**Smart improvised Question Answering System using BERT, LSTM and Semantic Structuring based on University’s dataset.**

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# Abstract:

Every large organization has a massive collection of documents that it can use to build a Question Answering systems to serve and solve the queries of stakeholders in that institute. Hence we propose a Question Answering System based on official documents available in a university. Although multiple solutions have existed for Question Answering systems. We are proposing the use of stacked layer of LSTMs (Long short term memory) to get the corresponding answer for the particular question where the words (tokens) are fed as input to the neural networks. We are using the BERT model for keywords extraction and feeding it to the LSTM neural net. This solutions is being built especially useful for Universities that have very large number of Normative and Directive documents. This solution can be used to quickly provide response to students’ queries whenever they visit the site without requiring them to visit individual sub components of the site. It makes the use of existing dataset in the organization while saving a lot of time for the students and staffs.

# Introduction:

Question answering is the branch of computer science that deals with building automatic systems that can provide answers to human generated Natural Language questions [79]. It is the blend of Natural Language Processing with Machine Learning techniques and Semantic Analysis [5]. Question answering system have come across a long way through since its initial inception in the early 1960s [80]. Initially, it used to be a simple single domain system trained on limited amount of data E.g.: LUNAR [80], BASEBALL [81], etc. The Gradually, as the sizes of knowledge bases(KB) grew larger and larger, more complex systems started to be developed that made use of more computation to process massive amount of data to develop more smarter QA systems[82]. First, there used to be linear models based Machine learning approaches like Support vector machines and Logistic regression and based on spare vectors of very high dimensions to solve the problems in Natural Processing domain [83]. Gradually, as technologies progressed and hardware became more capable, QA systems slowly progressed to non-linear models based on graphs, trees and neural networks.

On the basis of domain/scope of topics that the QA model addresses and responds to is divided into 3 major types: Closed domain QA and Open Domain QA. Close domain Question answering, as name implies, mostly have a narrow scope and are simpler while the open domain systems are comparatively more complex and require massive amount of data for training it [84].

A typical "Question Answering" model based on modern NLP techniques involves the following 3 broad steps while working on production: Question Preprocessing and Classification, Document Searching and Information retrieval, Answer Extraction, analysis and sentence generation [82].

In modern era, there are a lot of large organizations that have huge amount of structured and unstructured data in digital forms. Most of them are available publicly in the websites of the respective organizations while the others are internally maintained. These documents can range from norms, values of the organizations, code of conducts, rules, regulations and directions, etc. These documents can be a huge source of knowledge and information that we can use to build organization specific question answering system such that it resolved the queries of the students of the respective institutions. Building Question Answering Systems out of these is the most promising way to use and retrieve data from such knowledge bases by the end user [5].

It is a common problem faced by a lot of students that requires information are available on the university website but the students find it tedious to go through the site and into specific sub segment and get answer to their queries. It also takes a lot of their time and effort. Numerous solutions exist in this domain that are built for general purpose question answering but very few solutions exist that actually are made for specific type of documents like the strictly formal documents that organizations such as an university might have [7]. So, we are proposing a different model of question answering that specifically solves the problem in University and helps the students, staffs or anyone who might have some queries related to the institutions whose answers maybe be present in their documents or webpages.

For the solution to the chosen problem, we are using specially customized LSTMs with semantic structuring and BERT models for extracting the keywords. The extracted keywords will be sent to the customized LSTM layers and further processed to generate most probable and accurate answers to the queries passed. After the LSTM generated the most probable keywords in the answers to the questions, we further apply lemmatization and semantic structuring to form a sensible sentence using the keywords to give back reply to the user.

# Related Works:

For question answering (QA), the current state-of-the-art pre-trained models typically need fine-tuning on tens of thousands of examples to obtain good results [1]. Their performance degrades significantly in a few-shot setting (< 100 examples). To address this, one of the proposed solution was a simple fine-tuning framework that leverages pre-trained text-to-text models and is directly aligned with their pre-training framework [1]. The proposed few-shot fine-tuning framework design involves a different choice of input-output design and the training objective than the current standard for QA fine-tuning frameworks [1].

Question Answering (QA) is the task of enabling a machine to automatically answer questions posted by humans in a natural language form [2]. The selection of the best answer from an existing pool of candidate answers is referred to as community question answering (cQA) [2]. They extend the notion of interactive learning by developing a cross-sentence context-aware bi-directional LSTM model, where they generate the hidden representations for both the question and answer texts, thereby making them aware of each other’s context [2]. This has been discussed in detail by one of the reference papers.

[7] is making use of normative documents (i.e., formal documents that contain strict formatting and formal languages such as legal documents, agreements, rulebooks, affidavits, etc.) to build Question Answering System by performing interactive QA for highly precise results.[7][47] Reading such documents is hard. The name of the approach is Interactive Question Answering using pre-processed normative documents and algorithm used is Semgrex (Special version of regular expressions) [49]. So, they are building a chatbot is a kind of question answering (QA) system that enables answering users’ questions automatically.[48] To use the open domain systems in closed domain applications. [50]

[8] They are finding solution to train a Natural language-based Question Answering Model effectively and functionally in constrained scenarios where there is very less amount of training data [51][52]. The name of approach is Pseudo labelling with DistilBERT (transformers) for training QA systems with less data and algorithm used is Semi supervised learning-based pseudo labelling technique [53][54]. For that they trained a deep neural network in supervised manner simultaneously with labelled and unlabeled data [55].

[3] They have extend the boundaries of E2E learning for KGQA to include the training of an ER component as there are challenging problems in other datasets [56]. The proposed solution is approached as KGQA rely on semantic parsing (SP) to translate natural language into a logical form and algorithm used is RL (reinforcement learning) [57][58]. When compared with [59] they cannot be answered due to context ambiguity.

The paper [4] deals with the problem that creating datasets for Question Answers (QA) requires expensive hand-labelling work and specialized feature engineering. The focus of this paper is to collect more and better data that can maximizes model potentials [60][61]. The proposed solution describes their experimental setup, datasets, and then applies RWS to AS2-NQ and algorithm used is RoBERTa [62] and ELECTRA [63].

The objective of [10] in this paper was to provide a more effective data organization, management, and cognitive ability for the customer service business which other papers can’t do. [64][65] Therefore the proposed solution for this was Ontology construction and Construction of Knowledge Graph in the Field of Power Customer Service, algorithm used for this was BiLSTM-CRF. [66][67][68] Datasets used were 95598 electric power customer service business data. [69]

[15] Their work aims to narrow this gap by taking advantage of large language models and explores several factors such as model size, quality of pretrained models, scale of data synthesized, and algorithmic choices.[70][71] The proposed solution for the problem is a 3-step pipeline comprising of un-conditional answer extraction, question generation and question filtration and algorithm used is BERT, GPT-2, SQUAD.[72][73] Some datasets used are complex web questions. [74]

In the paper [13], they propose a novel simulation to real QA (Sim2RealQA) framework that completely trains a QA model with QA datasets produced in a life simulator and use it for solving real-word QA problems without answer labels. [75] [76] They proposed a novel simulation to a real QA (Sim2RealQA) framework that trains a neural QA model with many QA datasets produced in a life simulator and used it for solving real-word QA problems, algorithm used is RNN, DMN.[77][78]

To perform improvised Question Answering by building and querying SPARQL query templates [5]. It achieves higher efficiency than existing systems and makes good uses of large amounts of semantic data [5] available over the web. The algorithm used to issue this problem is Query Formulation algorithm in [5]. The solution is composed of two vital sections: Query processor [5] and Sparql query builder [5].

| **SQA Processes** | **Paper ID** | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **17** | **20** | **18** | **19** | **8** | **6** | **7** | **5** | **9** | **12** |
| **Process 1: Capture NL query** |  | | | | | | | | | |
| Simple question/non question form | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Process 2: Syntactic analysis** |  | | | | | | | | | |
| Part of speech tagging | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ |
| POS tagger and dependency parser | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ | ✗ |
| Stanford parser | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ | ✗ |
| Identify noun phrase/noun concept | ✗ | ✓ | ✓ | ✗ | ✗ | ✗ | ✓ | ✓ | ✗ | ✗ |
| Named Entity Recognition | ✗ | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ |
| Morphological analysis | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |  | ✗ | ✗ |
| Lemmatization | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ |
| Tokenization | ✗ | ✗ | ✗ | ✗ | ✓ | ✓ | ✗ | ✓ | ✗ | ✗ |
| Question Analysis | ✗ | ✗ | ✗ | ✓ | ✗ | ✓ | ✓ | ✓ | ✗ | ✓ |
| Question type classification | ✗ | ✓ | ✓ | ✓ | ✗ | ✗ | ✓ | ✓ | ✗ | ✗ |
| Syntactic sentence analysis | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| **Process 3: semantic analysis** |  | | | | | | | | | |
| Synonym | ✗ | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✓ | ✗ | ✗ |
| Homonym | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Hypernym | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| **Process 4: Syntactic and semantic linguistic disambiguation** | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ | ✗ | ✓ | ✓ | ✗ |

# Proposed Approach:

We have proposed the following model for the improvised Architecture model for the Question Answering based on BERT and stacked layers of LSTM, semantic and semantic structuring to serve the best answer corresponding to the given query.

## 3.1 Design of Architecture:

This research proposes a generic tool for decision-makers that would help the students of a particular university get answers to the common related doubts and question (FAQ) to their university. This could be an add-on (as a widget/ bot) to various university websites where this question-answering model can help to answer a student’s doubt almost instantly. This model is trained on a university dataset (self-created for this task) along with various popular QA datasets. Coming to the architecture this model is novel from any other existing architecture as this uses “keyword extraction” along with semantic restructuring to generate an answer to a particular question. You can see the proposed architecture below which uses BERT model to generate important keywords, feed them into a stacked LSTM network and then using semantic structuring to generate an appropriate answer to a question almost instantly.

Since there were no sufficient previously available datasets for our chosen problem domain, we created our own dataset to perform the experimentation and model testing. The dataset consisted of handpicked question-answer pairs extracted from the VIT University websites that included all different types of questions like the factoid Questions, list type Questions, casual type questions, confirmation type (Yes/No and True/False) Type Questions. The model was initially trained on a wide variety of datasets that included data from large datasets of formal style like the SQuAD from Wikipedia [86], Natural Questions (NQ) by Google, Question Answering in Context (QuAC), Conversational Question Answering (Coca) [87], HOTPOTQA [88], etc. Although most questions asked in the University’s FAQs will be closed domain (related to the University, administration, academics and system) factoid style (consisting of single answer and factual in nature, starting with [what, when, which, who.. etc.])[85], we made the model capable enough to handle the non-factoid questions as well just in case any such queries is put forward by the user while the model is running.

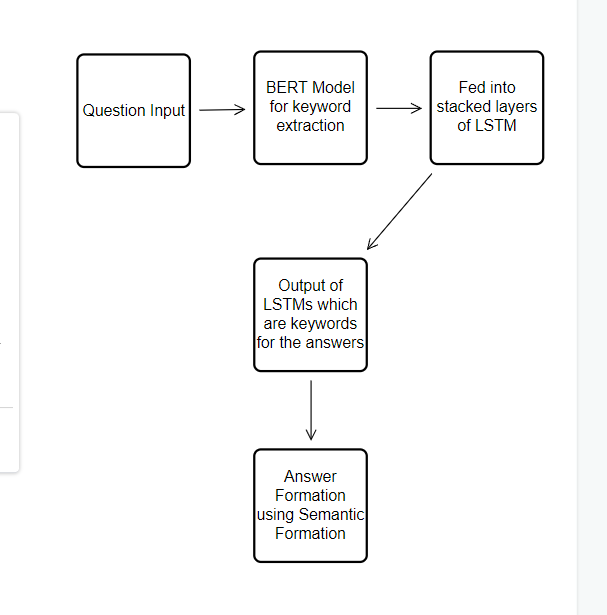


Fig 1: Simplified flow of the proposed model for Question Answering

## Datasets used:

We have used the following datasets for training our model:

* [SQuAD](https://rajpurkar.github.io/SQuAD-explorer/) from WikiPedia
* Natural Questions (NQ) by Google
* Question Answering in Context (QuAC)
* Conversational Question Answering (Coqa)
* HOTPOTQA

And for further testing it, we are also using a custom made dataset prepared by scraping data available on the university website. We are using BS4 and Scrapy libraries in Python to scrape the data and prepare it for testing the model.

# Experimentation:

The implementation of the proposed architecture consists of a BERT model to extract keywords (from the questions), then the use of LSTMs along with semantic structuring to generate the answer based on the output keywords from the LSTM (stacked neural network) We have trained and done the testing of the model using the university synthetic dataset which we have created to check its response and accuracy (metric like BLEU score and F1 score).

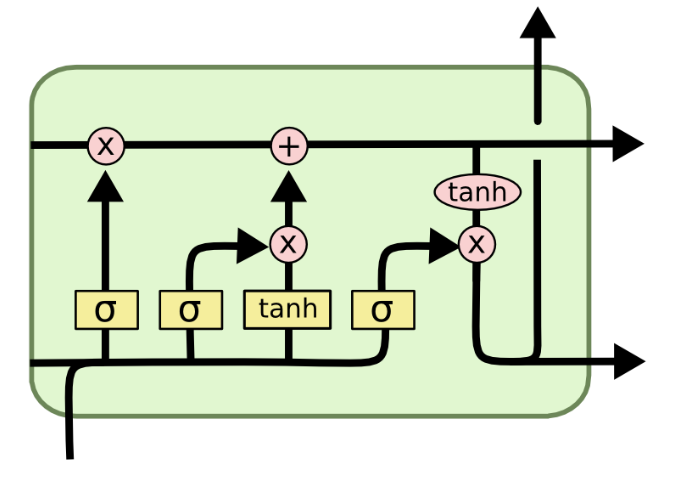
## 4.1 TRAINING

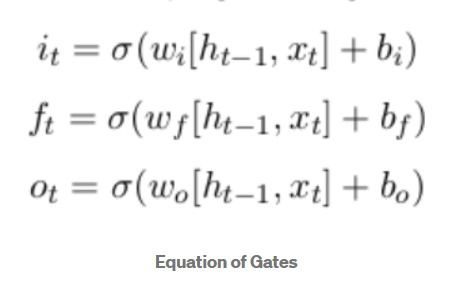
We train the model using the binary cross-entropy loss function:

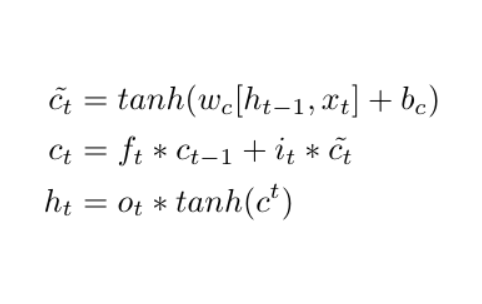
L(y, ˆy) = 1 NE X NE i=1 yi log ˆyi+ (1−yi) log (1−yˆi),

Where y ∈ R NE is a k-hot label vector.

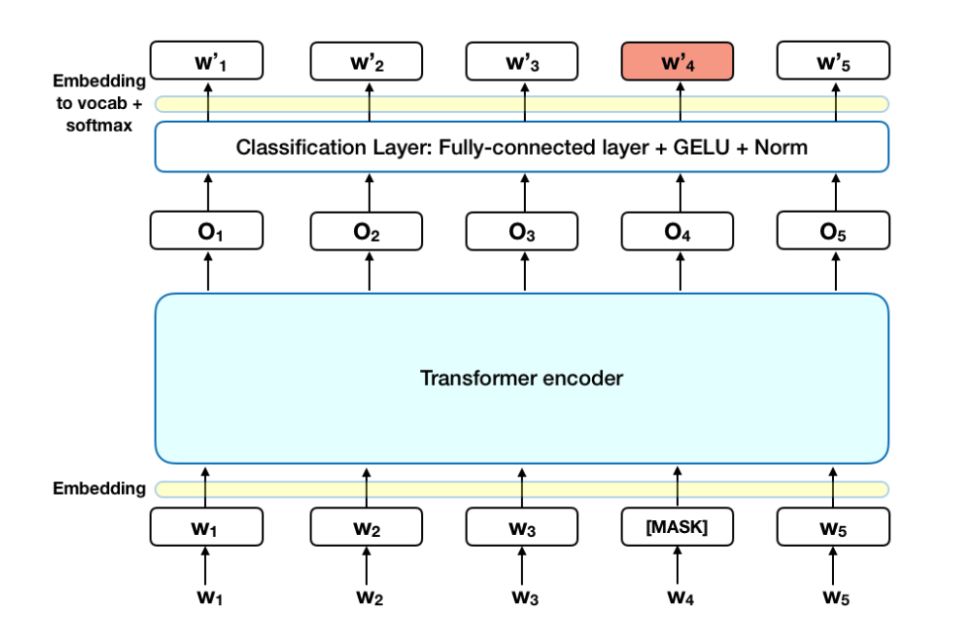
Apart from using BERT and semantic structuring, stacked layers of LSTMs are used to compute the keywords which should be present in the answer. Rather than a bidirectional LSTM model a Unidirectional model is used which uses the concept of backpropagation through time ( using gradient descent ) and binary cross entropy loss function defined above. Some of the equations of a LSTM layer to calculate the outputs during forward propagation are:







Standard BERT Model [50]:



The name of the model we have trained is called ASKE (Answer Segmentation using Keyword Extraction). Our current architecture currently is made up of three main parts which are the BERT model for keyword extraction, a series of stacked LSTM to output the necessary keywords to be present in the answer and then using semantic structuring to properly output the complete answer. Our architecture is a novel idea which gives us amazing results after the model is trained properly. To test our model we tested this on a university dataset . We use Adam optimizer with a learning rate of 2e5. We use a training batch size of 4. We don’t use learning rate scheduling.

## 4.2 Testing and Evaluation

To test our model infrastructure we have created a synthetic university dataset and used the training examples there to check the accuracy of our model (using the F1 score and BLEU score metric ). This gave us pretty amazing results on the dataset thus acting as a validation for our model. We also used word embedding to represent keywords generated from the BERT model which is then fed to the stacked layers of LSTM on top of each other. Each keyword generated from the question is fed to the neural network layers as an embedding matrix which is used to generate the keywords that should necessarily be present in the air. Below you will see the outputs generated by our model on the university synthetic dataset which we created and we can observer the model outputs are really amazing.

| Input | Output |
| --- | --- |
| 1. What is the nirf ranking of VIT Vellore? | 21 overall in India and 13 among Universities |
| 2. Where is VIT Vellore located? | VIT, Vellore Campus, Tiruvalam Rd, Katpadi, Vellore, Tamil Nadu 632014 |
| 3. How to get into VIT as an undergrad student? | Students must give an exam known as VITEEE |
| 4. What is the boy girl ratio in VIT? | Male to female percentage is found to be 74% : 26% in VIT-Vellore Institute of Technology |
| 5. What are chapters in VIT? | Chapters form for a variety of reasons such as: electing a central voice for issues that affect the entire class, to raise funds and to build a sense of camaraderie among classmates. |
| 6. What are the different types of mess available in VIT? | Special mess, Non-veg mess and veg mess |
| 7. Does VIT have a library? | Yes, it was named as Periyar Evar Central Library |

## 4.3 Comparison

| **Model** | **SQuAD** | **TriviaQA** | **NewsQA** | **HotpotQA** |
| --- | --- | --- | --- | --- |
| **BART** | **10.44±5.9** | **2.5±2.1** | **2.9±1.4** | **5.6±2.4** |
| **ASKE** | **10.52±5.6** | **2.4±1.8** | **2.7±1.2** | **5.8±1.9** |

*Comparison of F1 scores across all datasets for the standard QA fine-tuning objective (BART) vs the proposed aligned fine-tuning objective (). The value after ± indicates the standard deviation across 5 runs with different seeds. NQ stands for Natural Questions. TbQA stands for TextbookQA.*

# Conclusions:

The paper’s aim is accomplished and a practical, novel approach to build a Question Answering system based on University’s data available in their websites have been examined. The proposed approach made use of BERT model for keyword extraction and then stack of unidirectional LSTM based neural network for answer keyword extraction which was further converted to readable answer using semantic restructuring techniques. The proposed methodology has also shown really good results and stand against the major solutions for similar problems in open domain QA available today. This also helped us to make a good use of the university’s data- that is just stored on the websites to build a functional QA system for the convenience of students/faculties/staffs in the university.

# Future research - discussion:

Although the proposed system was functional and delivered answers to the user queries, it still has a lot of improvements and optimizations. We propose the following

* Fine tuning with even larger data.
  + The amount of data that we used for training and testing from the University’s website was simply minimal and not that enough. So there was some problem seen in the fine tuning of the model. So, as a further work of this paper, we have kept the fine tuning of the obtained model using even larger amount of data by scraping through entire website. It would lead to better and more accurate
* Implementing the model in the actual website.
  + The purpose of any research is to build actual product and make lives easier. Adhering to this principle, we have planned to implement the model as a FAQ answering system in the real website and serve the students in the university.

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