

Study And Modeling of Question Answer System Using Deep Learning Technique of AI

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Abstract— In this paper, the different QA system types, the theoretical foundation for deep learning models, the metaheuristic optimization techniques, and the performance assessment metrics are discussed. A suggested architecture for a question-and-answer system that takes a deep learning approach is shown here. The study also covers the constraints and factors to take into account regarding the aforementioned system.

Keywords- QA System, knowledge base, deep learning.

I. INTRODUCTION

QA systems may be defined as a technology that offers the correct short response to a question rather than a set of alternative responses. Figure 2.1 depicts the essential components of a question answer system.

A Question Answer System (QA) is a method that combines query analysis, document retrieval, and answer extraction into a single process.

Question Investigation Module:

To provide a suitable response, the system must evaluate and comprehend a user's question. At this level, the constraints and necessary keywords are retrieved together with the question's semantic content. The question analysis works with tasks like question categorization and named entity recognition. Based on the keyword, taxonomy, or task to be completed in the query that leads to the desired response type, the query is evaluated to reflect the important information required to answer the user's request. The query is evaluated to see whether it contains the crucial data required to respond to the user's question and get the intended result.

Module for Passage Retrieval:

The applicability of the knowledge base determines how precise a response will be. Finding a pertinent piece of information is crucial. During this stage, the knowledge base is scanned to identify pertinent texts or paragraphs.

Module for Answer Extraction:

For each new inquiry, the goal is to find the text and context. In a closed dataset, the context, which covers a continuous

time period, always includes the query's result. Once the sentence has been completed, this step determines the proper sentence and derives the correct response from it.

Data representations are vital to the QA system. Understanding a story or paragraph is a more important job since the target sentence and the query in figure 2.1 overlap. There are several QA system kinds, including WHY, FACTOID, and MCQ. The goal of this research is to utilise semantic classes to distinguish between various question types and provide the best model for answer choice based on the question type.

QA Domain Types:

Aside from the central architecture, each QA structure can be distinguished by the perception it employs.

Open Domain and Closed Domain:

This type defines the range of questions that a QA system can answer. Closed domain QAS is restricted to a domain, while open domain (ODQA) QA systems do not have this restriction. Open-domain structures can deal with almost any issue and focus solely on general ontologies and world knowledge. On the other hand, closed- domain architectures deal with questions that fall within a given domain and may use domain-specific information by fitting a model to a unique-domain database. For example, an ODQA created by Facebook Research draws on a vast database of Wikipedia articles as its knowledge base, whereas cdQA suit helps create a system based on specific applications like medicine, automobile, and education.

Type of Question Handled:

This attribute defines the types of questions that the machine can handle. The system generates the answer based on the kind of question. There are diverse categories of questions like factoid questions, list questions, Yes/No questions, times-based questions, general reasoning questions, complex questions, and questions expecting short or descriptive answers.

Knowledge Base:

This category of system is based on the organization of information and sources of information. The three main constituents are creating knowledge base by the semantic organization of information acquiring information from various sources to gain understanding to answer question finding the right source of information to answer user queries by integrating knowledge acquired from different sources.

The schemes most significant problem is the lexical difference between natural language and the knowledge base's formal semantics. Other challenge includes identifying the subject entity and linking to the knowledge base in the specified format. It becomes complex as the number of entities goes on increasing. Question- answer matching is challenging to tackle because it necessitates efficient representations of the complex semantic relationships between questions and answers.

Answer Processing:

These systems concentrate on the process of answer generation. Few systems identify and rank candidate answers according to user questions, while others focus on validation and compilation of answers. Some systems aggregate answers from various sources, and then the process of summarization and generation is carried out.

Question Analysis:

The quality of the input determines the success of any machine learning algorithm. Specifically, the peculiarities of the circumstance at hand. Feature extraction is required for understanding and modelling physiological data. Expert knowledge is traditionally used to choose hand-crafted features that are then utilized for classification or regression. Identifying key attributes and selecting the most effective ones for a new job may be time-consuming and labor-intensive. Furthermore, whether dealing with new or large-scale tasks, the manual approach is inefficient. In case of text processing tasks like question answer system the features are the words contained in any document their association with each other to generate meaning. To begin training on these documents, any supervised machine learning method requires that each textual document be represented as a vector using Vector Space Modelling (VSM).

Discourse integration is an important feature of text pre-processing because it concentrates on the qualities of the complete text that express meaning by connecting individual phrases. It relates to the context of the incident. Discourse Integration is impacted by the sentences that before it as well as the meaning of the ones that follow it. We have incorporated WordNet lexical database for encompassing world knowledge.

The proposed method extracts and integrates lexical, context Similarity features, syntactic and statistical features based on the literature surveyed. Along with these feature question adaptation features are also extracted for intent detection. We notice that by combining lexical, syntactic, semantic, statistical, and task adaption data into a single form, we may obtain richer characteristics for choosing the proper target label for each query.

Question Intent Detection:

The most difficult job in developing a QA system is determining the exact objective behind a query. Question intent classification is the process of classifying the user's intent by analyzing the passage and the question asked. To accurately categorize a question, the system must first determine what the question's objective is, what the limitations are, and what the available replies are. Question intent classification is a discourse integration of past ,present and future actions. The system needs to select an answer from available answer set which is more appropriate. The answers generated by any Question Answer system is broadly classified as short answers and descriptive answers.

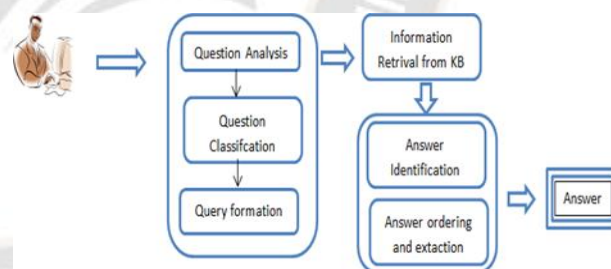


Figure 1: Basic QA system

The short answers are further divided as yes/no, list, entity, description, person/object, location, numeric values etc. Categorizing short Wh questions depending on basic three essential parts viz. context or intent, time and space reference. The question structure is examined in order to find the base class. Question Structure helps to identify user motive or intent and correctly answer user question. Every question has 3 dimensions viz. Question Type, Answer Format and Answer Theme There are different types of questions like general reasoning question like “Why do we need water?”. These questions start with “Why” and expect a brief explanation as an answer. Questions containing head words like “Who is

...?”, “How many ...?”, “What is....?”, “Where is...?” require a person, number, time and place or location as an answer.

TABLE 1 ANSWER AND QUESTION TYPE

Answer Type	Class	Subtypes
ABBREVIATION	ABBR	abb, exp
ENTITY	ENTY	Animal, body, color, creativity, food, language, plant, sport, vehicle, religion, letter, event
DESCRIPTION	DESC	Definition, description, manner, reason
HUMAN	HUM	Group, individual, title
LOCATION	LOC	City, country, state, other
NUMERIC	NUM	Value, temperature, count, size, money, weight, percent, temperature.

Words like Define, compare, contrast, summarize, classify require a short explanation about the theme of question. On other hand, questions like multiple choice, Yes/No, True/False require a selection of one of the given options as answer. These questions contain a main verb, main noun and a preposition in its formation. For example, a response to the question “Who was the first person to land on moon?” will be a person’s name, while “Where is Taj Mahal located?” will be a place. Thus, identifying the answer requirement, the system needs to detect named entities to identify a name of person or place. On the other hand, “What is Teflon coating?” expects a brief description as an answer which may be a sentence or a fragment of sentence.

There are several varieties of factoid inquiries that begin with when, what, where, and who and may be answered in a sentence or a single word. How and why, on the other hand, are non-factoid queries that need a technique, logic, and a reasonable explanation in the answer? Aside from that, there are other types of questions that are context-dependent and must be identified for domain-specific systems. The aim of Question intent identification is too minish the searching space by defining appropriate searching strategies and context.

The main hurdle in identifying the intent behind the question is its short length with only lexicon-based information. To obtain higher accuracy, the syntactic and semantic information needs to be clubbed with extended vocabulary of question including semantic meaning of every word. As stop words like “what” and “is” play a crucial role in identifying the intent behind a question, Bag of word method is used to create

dictionary of words. Word spellings indicate word form in WordNet, while Synsets communicate meaning, and each synset represents a notion. Both lexical and semantic associations are displayed in WordNet. Between word forms, the former exists, while the latter exists between concepts. We chose hypernyms between nouns as our primary interest among the many semantic links in WordNet. The senses of the nouns in the sentences and the Synsets of their hypernyms are the distinguishing characteristics. As a distinguishing feature, the N gram model with bigrams and trigrams is chosen. There is different type of intents behind a question.

Result and Discussion

Deep learning Approaches:

Deep learning, uses numerous layers of heterogeneous type $i * n$ networks to allow for practical application, efficient implementation, trainability, and understandability. Deep neural networks (DNNs) will extrapolate high-level characteristics from original data using statistical learning to generate a usable representation of the input space on enormous data. Three types of deep learning systems are found: unsupervised, semi-supervised, and supervised: CNN, GRU, RNN, Deep Belief Network (DBN), Restricted Boltzmann Machine (RBM), and Self- Organizing Map (SOM), Autoencoders (AE) are the famous architecture of deep learning.

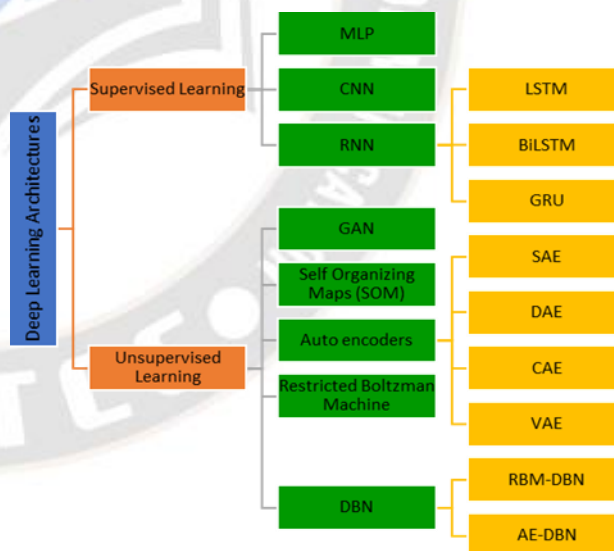


Fig 2 Deep Learning Architectures

Recurrent Neural Network:

An RNN is a form of artificial neural network (ANN) which can accommodate multiple inputs and has no size restrictions. The model aids in the summarization of previous data and its transmission to the next state. However, due to the vanishing gradient problem, RNN cannot use future context due to memory loss. In addition, RNN suffers from long-term

dependencies. GRU and LSTM are two RNN advancements. LSTM learn to safeguard the memory cell's continuous error flow from fluctuations caused by irrelevant inputs.

Restricted Boltzmann Machine

The components of a limited Boltzmann machine are an input layer, as well as a hidden layer. There is a connection between all of the neurons in the input layer and the neurons in the hidden layer. During the training phase, RBMs use a stochastic method to compute the probability distribution of the training sample. This calculation takes place using the training sample. When the training first starts, the stimulation of each neuron is completely at random. In addition, there is a mixture of unconscious and explicit bias across the network. In addition to being generative models, they are capable of reducing the dimensionality of data and participating in collaborative filtering.

Deep Belief Network (DBN)

Hinton et al.[15] introduce DBN (deep belief networks) by demonstrating that RBMs may be layered and trained greedily. A DBN is a form of DNN with many hidden layers. Such a network examines connections between levels rather than units at these levels. A DBN comprises many Restricted Boltzmann Machines (RBMs) stacked on top of one another. A stochastic recurrent neural network, or RBM, comprises layers of visible and hidden units. These hidden nodes identify the higher-order data correlations represented in the visible layer. A network of proportional weights connects different types of weights.

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