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Different Facets of Text Based Automated Question Answering System

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***Abstract*: The exponential growth of online information has led to the development of technologies that help to deal with it. One of those information retrieval technologies is Question Answering (QA), a research field that has emerged at the intersection of information retrieval and natural language processing techniques, which allows users to find the answers to their questions in precise way. However, to cope up with changing needs of user, the recent QA system differ widely in the manner they interact to the user than the conventional one. Therefore, this paper attempts to present the state-of-the-art in the field of text based automatic question answering systems and provide a qualitative analysis of different facets. Finally, a summarized representation of these facets based on certain features of QA system has been done, to bring an insight for the future research.**
Keywords: ***Automated, multilingual, Interactive, question answering, community.***

I. INTRODUCTION

In the beginning of Automatic QA, efforts were made to ease man-machine interaction. It evolved from simple interaction systems without a knowledge database relying on a domain specific to complex systems, which are web-scaling and able to answer elaborate questions in an interactive and context based way. Normal key word based search engines rely on the replying of a set of relevant documents to a specific query. As the information amount is constantly growing in the internet it can be hard to find correct information, so there should be possible way to get specific answers to a query.

Automatic QA is a huge field of diverseness. There exist many different concepts of analysing the question with computational linguistics and natural language processes, retrieving the documents and extract relevant information for the answers, mapping the documents to the answers or to reply to the user and the interaction with the human. The popularity of social media has grown in the recent years. For some social media platforms the alternative search has built an effective counterpart to the usual web search. For Automatic QA social media platforms offer a good field of activity. With its closed system and the large datasets it is possible for Automatic QA systems to easily answer questions about e.g., user activities, hobbies or preference.

The systems participating in the TREC QA [1] track up to some extent have similar number of features and technologies, and in generalized view the whole design of the systems in most cases can be considered remarkably alike. An automated QA system based on a document collection typically has three main components: question processing, document processing, and answer retrieval. An illustration of this prototypical system architecture is shown in figure 1.

A. Question Processing

Question processing fundamentally consists of pre-processing of question which may involve tokenization, chunking, shallow/ deep parsing derivation of expected answer type (e.g. person, definition) and keywords extraction which are later on submitted to the information retrieval system. In recent times, systems also perform question reformulation, where a question is transformed into a number of equivalent queries to identify various ways of expressing an answer given a natural language question. Parsing is done in order to construct some form of structural illustration of the question with the help of syntax. The extracted keywords are used by extraction engines to fetch relevant documents. The expected answer type is also derived for this purpose.

B. Document Processing

Document processing involves keyword expansion, document retrieval, and passage detection. Keyword expansion typically involves taking the keywords fetched in the question processing stage and looking them up in a thesaurus, or other resource, and adding similar search terms in order to retrieve as many documents as possible.

C. Answer Processing

Answer selection component extracts candidate answers and select most appropriate one, as specified by the question analysis component. A text based similarity metric combining lexical, syntactic and semantic criteria is applied to the query and to each retrieved document sentence to identify candidate answer sentences. Candidate answers are ordered by relevance to the query and list of top ranked answers is returned to the user. While most of the question answering system presents answer as it was found in the relevant document, some systems also perform answer formulation with the help of question processing module.

Beside these components, designed architecture has some other essential components as:

1) *Document Collection:* Document collection component described in figure 1 actually refer to the information resource (structured, semi-structured or unstructured) viz., knowledge base, comprehension text, document collection or web data whichever is utilized by the QA system for the extraction of candidate answers.
2) *Domain Knowledgebase/Lexicon:* Domain information is saved in the knowledgebase or lexicon to find semantic relation among keywords, so that system can analyze questins and answers semantically.

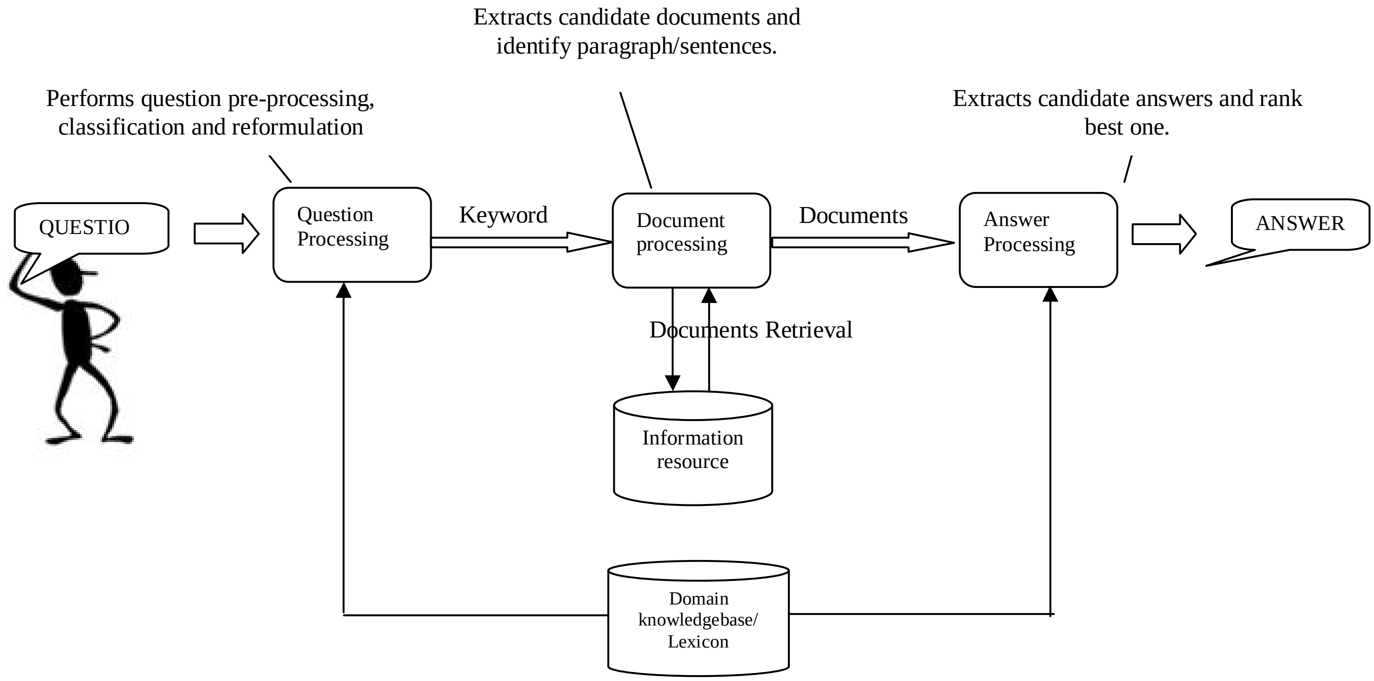

Fig 1: Question answering system architecture

II. HISTORICAL DEVELOPMENT

Research and development in the field of systems capable of answering questions in natural language started with one of the earliest and best known Artificial Intelligence (AI) dialogue systems as Weizenbaum's ELIZA [2]. ELIZA was designed to emulate a therapist and operates through sequences of pattern matching and string replacement but it was not a robust dialogue system as many times it produces complete garbage due to strictly applying transformation rules. Another successful system of its time was BASEBALL, by Green et al. [3]. The BASEBALL system was designed to answer questions about baseball games which had been played in the American league during a single season. Another example of a natural language database front-end was the LUNAR system, by Woods [4]. The common feature of all these systems is that they had a core database or knowledge system that was hand-written by experts of the chosen domain. In earlier days, many prominent research works have been done in the field of question answering system and their contribution cannot be ignored. However, here we are going to discuss only ELIZA [2] and SHRDLU [5] considering their important role during evolution of these systems.

Since the early days of Artificial Intelligence in the 60's, researchers have been fascinated with answering natural language questions. However, the difficulty of natural language processing (NLP) had limited the scope of QA to domain-specific expert systems. These systems include front-ends to structured data repositories, conversational question answerers and systems which try to find answers to questions from text sources, such as encyclopaedias. Some of these systems are tabulated as below:

TABLE I. Some QA systems during the evolution of QA system.

QA System	Year	Developer	Domain	Description
BASEBALL	1961	Green et al.,[3]	Baseball game	answering questions about baseball games played in the American league over one season
ELIZA	1966	Weizenbaum et al.[2]	Medical	was a dialogue system and to emulate a therapist
SHRDLU	1972	Winograd[5]	Toy	SHRDLU was built for a toy domain of a simulated robot moving objects in a blocks world
LUNAR	1973	Woods et al.[4]	Lunar rocks	answering questions about lunar rock and soil composition that was accumulating as a result of the Apollo moon mission.
MARGIE,	1975	Shank et al.[6]		was capable of reading and interpreting a document, and answering a series of questions.
GUS	1977	Bobrow et al.[7]	Airlines	simulated a travel advisor and had access to a restricted database of information about airline flights.
LILIOG	1991	Herzog, Rollinger[8]	Tourism	Was a text-understanding system that operated on the domain of tourism information in a German city.

Research in QA has been accelerated due to the inclusion of a QA track by Voorhees at the Text Retrieval Conference (TREC) since 1999. Since then, increasingly powerful systems have participated in TREC and other evaluation for QA systems such as CLEF and NTCIR. The availability of huge document collections (*e.g.*, the web itself), combined with improvements in information retrieval (IR) and NLP techniques, has attracted the development of a special class of QA systems that answers natural language questions by consulting a repository of documents.

Current research works in QA are now focusing on retrieving answers based on the activity of filling predefined templates from natural language texts, where the templates are designed to capture information about key role players in question. Some concurrent pioneer work in the field of Question Answering (QA) system may be summarized in the below table as:

TABLE III. Some prominent QA systems in recent past

QA System	Year	Developer	Description
IBM's statistical QA	2000	Ittycheriah et al.[9]	This system utilized maximum entropy model for question/ answer classification based on various N-gram or bag of words features.
MULDER	2001	Kwok et al.[10]	wasfirst fully automated, general purpose QAS to generate response from web with less user effort.
START	2002	Katz et al.[11]	Developed by MIT Artificial Intelligence Laboratory, was the first system that can access large amount of heterogeneous data by integrating structured and semi structured web databases into a single, uniformly structured virtual database.
Question Assistant	2002	Sneiders[12]	Designed on the basis of templates so that single template could cover a wide range of data instances relevant to the entity slot and almost all questions of its type.
YorkQA	2004	Marco De Boni[13]	examined expected-answer type merely in a different way i.e., from philosophical point of view to a QA system and try to determine expected answer type in relation to a question.
ASQA	2008	Lee et al.[14]	The ASQA has used surface patterns for biography questions and entropy methods to deal with definition and relation questions.
WATSON	2010	Ferrucci et al.[15]	WATSON competed against human grand champions in real time on the American TV quiz show *Jeopardy!*

III.DIFFERENT FACETS OF TEXT BASED AUTOMATED QUESTION ANSWERING SYSTEM

Since evolution till date, automated question answering system has acquired different facets to meet the changing requirements of user. Recent systems are not only enhanced to present answers in more than one language (multilingual) but many of them have also implemented analytical approach(community based)to previous answers of a question to have more refined and accurate answer according to user's interest in real time (interactive).In next section, we are going to present the diverse facets of automated question answering on behalf of the mechanism acquired to interact with user while giving the expected response.

A. Standard Question Answering System

Most common QA systems those existed so far are monolingual question answering system. Such systems receives question in one language and delivers response in the same language. Most of the systems discussed in related work section belong to this category only. These QA systems might implement different procedures and utilize different resources for extracting answer but will present answer only in the asked language. Main aim of such QA systems is to enhance accuracy of the response rather bothering about enhanced user friendly features. Such features may include presentation of extracted answer in language of user's choice and that too in real time. In addition to the standard QA functionality, implementation of these features would require consideration of different language structure, anomalies and time constraint.

B. Multilingual Question Answering System

Multiingual question answering as name suggests is a sub-field of question answering that not only allows user to have answer in the asked language but also in other languages. The multilingual version of automated question answering hasn't gained much attention during earlier days of question answering. Earlier QA systems had only focused on presenting answer in English language. However, with the enhancements of natural language processing mechanisms, later systems started focusing on development of cross-lingual QA systems that allow access to information in non-English language. Cross-lingual (Bilingual) QA systems can be considered as extension to conventional QA research while multilingual can be considered as extended version of cross-lingual QA. Beside following the standard mechanism of QA system development, multilingual systems has main focus on mapping of different language structures, semantics, sense disambiguation and existing anomalies. These tasks become much tedious due to inherent difference existed in representation of syntax and semantics of considered languages. Majority of such QA systems developed so far aims on translating relevant section of the question usually with the help of machine translating systems. This translated text is later on used to access a collection containing relevant information. Most of the popular multilingual QA systems greatly rely on monolingual QA systems to extract relevant response to the question. Likewise, monolingual counterpart, it depends greatly on good corpus and database. Additionally, external lexical resources also plays important role while dealing with different language structures. The JAVELIN [16] system is a modular, extensible and language-independent architecture for building question-answering systems. The system was earlier developed for English version and now it has been extended for cross-language question answering in Chinese and Japanese. The system has evaluated the two modules English-to-Chinese (EC) and the English-to-Japanese (EC) separately as a subtask for gold standard data at NTCIR, CLQA evaluation. The work concluded that keyword translation accuracy grealy affects overall performance on the CLQA task.

Power Answer [17], an open-domain Question answering system is presented by Language Computer Corporation (LCC). The paper reports Power Answer participation at QA@CLEF 2007, where it is integrated with its statistical Machine Translation engine for English-to-French and English-to-Portuguese cross-language tasks. Intermediate processing has been performed only in English regardless of the input or source language and mapped back to the source language documents for final output.

Garcia Santiago et al., [18] has analysed the effectiveness of the translations obtained through three of the most popular online translating tools (Google Translator, Promt and Worldlingo). Evaluation has been performed on the basis of automatic and subjective measures. The results reported that the tools and linguistic resources used by automatic translators for German-to-Spanish translations are more limited and less efficient than the French-to-Spanish online translators. The work presents a comprehensive way for understanding online translators and their prospective in the context of multilingual information retrieval.

Olovera LOBO et al.,[19] analyzed HONqa, QA multilingual biomedical system available on the Web using set of 120 biomedical definitional questions (What is...?), taken from the medical website WebMD, which were formulated in English, French, and Italian. MRR, TRR, FHS, precision, MAP evaluation measures have been used for analysis. Though, result was evaluated in multilingual environment but the English language achieve better results for retrieving definitional information than in French and Italian.

Forner et al., [20] offers an overview of the key issues raised during the seven years' activity of the Multilingual Question Answering Track at the Cross Language Evaluation Forum (CLEF). The work summarizes testing of both monolingual and cross-language Question Answering (QA) systems that process queries and documents in several European languages,concerned challenging issues, created data sets, different types of questions developed and main evaluation measures utilized.

Eby et al.,[21] has analyzed the main publications from 2000 to 2010 related to multilingual question answering. The survey has identified various information resources, tools and techniques used during this time span. Most popular resources were databases, dictionaries, corpora, ontologies, thesauri, Wikipedia and Euro WordNet while popular linguistic tools were computational grammars and automatic translators. Parallel corpora and machine translation have remained as most popular techniques for cross lingual analysis due to low computational cost and ease of storage.

BRUJA [22], a multilingual QA system developed for English, Spanish and French languages.The BRUJA architecture uses English as Interlingua to make usual QA tasks such as question classifications and answer extractions. Cross Language Information Retrieval (CLIR) techniques are used to retrieve relevant documents from a multilingual collection. Increased number of documents, however, also poses threat of introducing noise to the retrieved information. The issue has been addressed by 2-step RSV merging algorithm for passages in multilingual QA.

QALD-3 [23] is the third version of the open challenge on Question Answering over Linked Data participated at CLEF 2013. The system has a strong emphasis on multilinguality, offering two tasks: one on multilingual question answering and one on ontology lexicalization.

C. Community Question Answering System

Automatic question answering (QA) deals with automatically answering questions that are formulated by humans in natural language. Usually, these systems are good at answering factoid questions (What is cost of iPhone7?) instead of complex non-factoid questions (What do you think about features of iPhone7?). Obviously, answer to such questions cannot be found in pre structured knowledge bases. Also, most of the fact based question answering system and digital assistants fail to provide answer for most of such questions. On the other hand, famous Community Question Answering platform such as Stack Exchange [47] or GuteFrage.net [48]allows users to ask any type of question related to some specific topic which in turn answered by another user using same platform. In recent times, CQA archives have become a rich information source for non-factoid questions[24].These communities explore themselves with the help of small number of highly active user viz., experts, which provide high quality relevant answers. These expert users nurtures the community and expert identification techniques are used to retain them in community which often need more analysis and elaborated text to provide correct response. This research field is closely related to natural language processing (NLP) as well as information retrieval (IR).

Cassan et al., [25] developed Priberam's QA system that relied on their earlier developed multilingual semantic search engine. However, system has used its own indexing technology LegiX, a legal information tool instead of third party indexation engine used in earlier work. The indexing engine provides indexing to semantic information, ontology domains, question categories and other specificities for QA. Initially the system was tested for Portuguese module but later on also adopted for Spanish language. The work described in paper emphasized on the improvements and changes implemented to adapt Spanish language along with Portuguese for cross-lingual extension. Liu et al., [26]has worked on issue of predicting information seeker satisfaction in collaborative question answering communities. A prediction model has been developed to predict whether a question author will be satisfied with the answers submitted by other community member. The task also includes development of variety of content, structure, and community focused features. Information seeking patterns that lead to user satisfaction is also identified for question answering communities.

ASQA [27] is a community QA system developed with the aim to answer subjective questions. Therefore, key task of system involves identification of question subjectivity, which identifies whether a question is subjective or not. The proposed work has collected training data automatically by utilizing social signals in CQA sites without involving any manual labelling. Implementation involved data driven approach using manually labelled data and an improvement is also reported after using heuristic features for question subjectivity identification. Anderson et al. [28] has analysed dynamics of community activity for stack overflow[46], a question answering site. The analysis is based on set of answers, both how answers and voters arrive over time and how this ultimately affects outcome. The work has also proposed a probabilistic model that captures the selection preferences of users based on the questions they choose for answering. The results claimed that experts and potential experts differ considerably from ordinary users in their selection preferences and hence could be identified with higher accuracy using machine learning methods and be further improved if applied in conjunction with several baseline models.

Liu et al., [29] has worked on predicting popularity of question in CQA by implementing statistical analysis on different factors affecting the same. A supervised machine learning approach has been proposed to identify factors influencing question popularity. Such factors can distinguish the popular questions from unpopular ones in the Yahoo! Answers question and answer repository. Baltadzhieva et al., [30] has reviewed existing research on question quality in CQA websites. The work discussed various features affecting the quality of asked question. Such analysis of features are useful for forums to help users in formulating improved question so as to retrieve most prompt information they are searching for.Zhao et al., [32] considered the problem of expert finding from the view point of learning ranking metric embedding. The ranking metric network learning framework has integrated users' relative quality rank to given questions and their social relations for expert identification.
Srba et al., [31]has reviewed 265 articles published between 2005 and 2014 related to Community question-answering (CQA) and presented a comprehensive state-of-the-art survey. They have proposed a framework that defines descriptive attributes of CQA approaches and their classification with respect to problems they are aimed to solve. As a part of the survey, the study also highlighted current trends and the areasthat need to pave further attention from the research community. Song et al.,[32] aimed at non-factoid question-answering that usually expects passages as answers. A sparse coding-based summarization strategy has been proposed that includes three core features: short document expansion, sentence vectorization, and a sparse-coding optimization framework. Each answer is extended to have more comprehensive representation based on such features.

D. Interactive Question Answering System

Interactive question answering allows users not only to have answer to their asked questions but also the related information. These systems somehow give response in a manner as if interacting to a person in real environment. These systems establish a communication to assist user by either suggesting related information or providing refinements to the user's query. In other words, an interactiveQA can be defined as a question answering mechanism that sets up at least one communication between user and the system and the user has some control over the rendered information and the actions taken afterward[33]. Such systems are quite similar to the text based dialogue system built upon mechanism of question answering systems [34]. Interactive QA systems are capable of answering complex and non factoid questions along with factoid questions in real time. The complex interactive question answering has been included in TREC track since 2006 (TREC 2006 question answering track) that has been also continued in 2007. Initially, the Quarteroni et al., [35] has proposed the design and implementation of a chatbot-based interface for an open domain. Though, later on anaphora resolution strategies are used to achieve real time interaction in response to the user's query. Anaphora queries are text occurrences where a noun (known as the anaphor) has been replaced by a word or phrase (known as the referent) which refers directly back to a previous occurrence of the missing noun.
E.g., **Q**: Who is Michael Phelps? **A:** a retired swimmer and most decorated Olympian of all time, with a total of 28 medals. **Q**: Which country does he belong? In this exchange the anaphor is "Michael Phelps" and the referent is "he".
HITIQA [36] is one of the major initial efforts based on interactive question answering technology. The system allows users not only to pose questions in natural language but also assist them in performing their task. The focus of designed to allow the user to submit exploratory, analytical, non-factual questions, such as "What has been Russia's reaction to U.S. bombing of Kosovo?" Obviously, such type of diplomatic questions need further communication to know what exactly user is intended to ask. Therefore, the HITIQA dealt with such questions by developing frames covering different classes of events, from politics to medicine to science to international economics, etc. Harabagiu et al., [37] has presented an interactive QA system, FERRET based on predictive questioning. The system makes use of a QA architecture that integrates QUAB (question-answer databases) question-answer pairs into the processing of questions. QUABs are created off-line and their use has greatly improved the overall accuracy of an interactive QA dialogue as they provide access to rapidly adopted users valid suggestions.
Hickl et al., [38] described a methodology for enhancing the quality and relevance of suggestions provided to users for interactive QA systems. The system combines feedback from users with Conditional Random Fields based classifier to enhance the quality of suggestions. The system achieved nearly 90% F-measure by combining the information a user's interaction with semantic and pragmatic features derived from the structure and coherence of an interactive QA communication.
The RITEL [39] system has been developed by Rosset et al., initially as a speech-based IQA system. However, later on a text-based interface to the system is developed to allow interaction through a web browser. The performance of RITEL system is evaluated as separate task for both spoken and textual input [40]. The results indicate that while users do not perceive the two versions to perform significantly differently, but more rigorous search is possible in a typical text-based dialogue. IQABOT [41] is an extension to pre-existing question-answering services which focuses on pronominal anaphora resolution in follow-up factoid queries. It will allow a natural discourse to take place by emulating the behaviour of chatbots [42] that are "conversational agents, providing natural

language interfaces to their users. The agent plays key role at interactive layer and rectifies the user's mistake while formulating complex queries.

Liu et al.,[43]has developed an IQA which extracts answer from FAQ knowledge base which is extracted from community question answering web portals. The syntactic, semantic and pragmatic features between question and candidate answers and context information are used to construct models by ranking learning method to extract the answers. The system has utilized user's feedback to the retrieved answer as a naive method for interaction. Konstantinova et al., [44] has developed an IQA that helps customer in process of deciding better product based on different features. The system establishes a dialogue with the customer when their needs are not clearly defined. For this purpose acorpus-based method is proposed for weighting the importance of product features depending on how likely they are to be of interest fora user. For further enhancements, asentiment classification system is also employed to distinguish between features mentioned in positive and negative contexts. Schwarzer et al., [45] presented an information retrieval-based question answering (QA) system for the large German e-government domain. The system successfully handles ambiguous questions by combining retrieval methods, task trees and a rule-based approach.

Table 3 gives a comprehensive overview of different facets of automated text based question answering system based on different key features.

TABLE IIIII. Summarized representation of the different QA systems

	Standard QA	Multilingual QA	Community QA	Interactive QA
Question type	Single sentence questions (Mostly factoid).	Single sentence questions in different accepted language	Multi sentence questions (Usually non-factoid).	Series of single sentence questions to have better understanding of the subject.
Question Reformulation	Automatic	Automatic	Manual	Automatic but user guided
Question Understanding	Depends on techniques (Shallow or deep linguistics) implemented	Depends on techniques implemented.	Depends on the understanding of community members responding to the asked question.	Good understanding as question representation is improved by real time interaction.
Answer Resource	Corpus, Knowledge base, Web documents	Corpus, Knowledge base, Web documents available for different languages	User (Expert) generated	Corpus, Knowledge base, Web documents
Answer representation	Short	Short	Long answers (or as required to the question)	Mixed answers
Answer reliability	Usually high	Average	Depends on potential experts	Average
Time lag	Immediate	Immediate	Have to wait until an answer is posted.	Real time response

IV. FUTURE DIRECTION

From the systems and techniques we reviewed in above section, we can observe a shifting of trend from conventional QA systems that are most suitable for factoid questions to complex one capable of answering non-factoid questions too. Each facet of QA, viz., multilingual, interactive or community is mere extension of constraints available in conventional model. Multilingual QA system breaks the language barrier and paved the way for research in direction of such future systems that can accept question in any language. Similarly, focus of interactive QA systems is user satisfaction in real time. These systems suggests user to put their questions in most prompt manner by establishing an interaction between the two. This is the reason why IQA systems are less likely to have to deal with ambiguous language constructions such as prepositional phrase attachment or complicated syntactic structures.

Moreover, when an IQA system encounters such an ambiguous construction, it can interact to user to clarify the user request. Therefore, complex question can also be posed to IQA and user is not restricted to ask only single sentence question. Community question answering gives freedom from asking questions to a specified format and allow user to ask question in any human understandable format.

Though, internal processing of multilingual and interactive QA differs widely, but their performance is highly dependent on good information source. Performance of all of the QAS is also affected by the psychology and the skill of the user. Interactive QAs provide solution to this issue but a better framework is required that can track the browsing history and behavioural activities of users and present answers in more effective way. Multilingual QA systems still require better algorithm to deal with heterogeneous multilingual data collections and porting techniques for QA systems of different languages. Community QA has effectively allowed information seekers to obtain specific answers to their questions but, it may also take hours or sometime days until a satisfactory answer is posted.

V. CONCLUSION

In this paper, we surveyed different versions of existing QA system that are available to handle the varying needs of user. We have seen an evolution from earlier simpler model that often answers in constrained environment to the complex one and free from semantic, structural, lingual and time constraints. As a result of survey, we have found that though question answering task has been exploring itself successfully for multilingual and interactive platforms, but pace of research studies for community QA is more popular and faster. The reason for this biasness lies within the requirement of less automatic processing and more human intervention while searching for relevant information.

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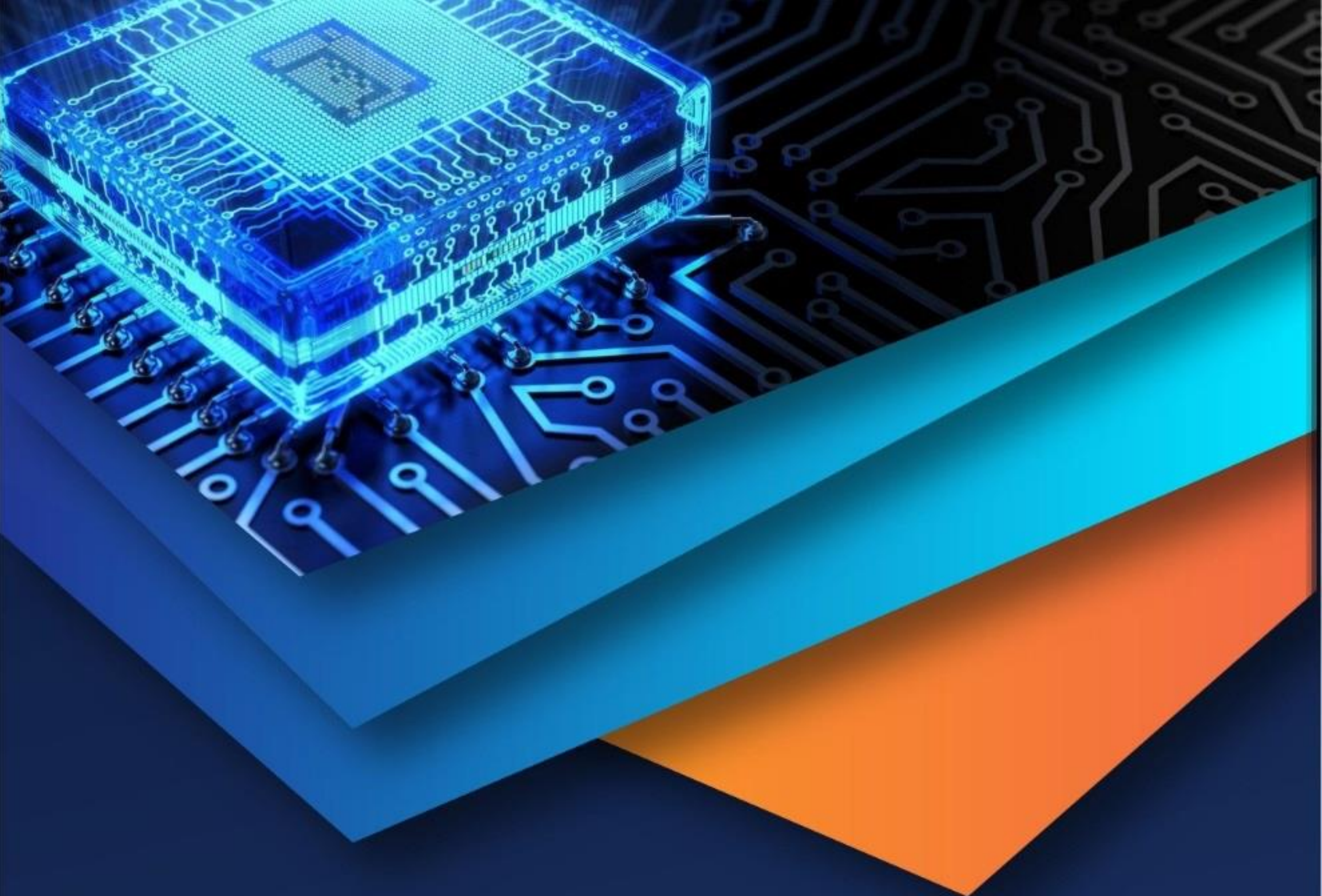

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