International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 06 Issue: 02 | Feb 2019 www.irjet.net p-ISSN: 2395-0072

SURVEY ON INTUITIVE RESPONSE SYSTEM FOR SMART CAMPUS USING AMAZON ALEXA

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Abstract - *A device that could make smart campus by providing the assistance on the information about the campus is to be designed and developed. The Alexa-enabled wireless smart speaker is the gateway for all voice commands submitted to Alexa. Amazon Echo is not only a smart speaker, but operates as an intelligent personal virtual assistant. Alexa has been programmed with information about events, specific locations, college hours of operation and other general information about the campus. Users can interact with Alexa to find out which events are scheduled, on which information about the faculty and students are provided. Alexa then lists the event on offer. Therefore, users can ask Alexa to explain what specific events are about to see if they want to attend.*

Key Words: **Alexa, Cloud Computing, AVS Services**

1. INTRODUCTION

In recent years, more Digital Voice Assistant (DVA) devices are deployed in each and every field. The enormous efforts of the leading DVA device manufacturers (e.g., Amazon and Google) and the third party voice service developers (e.g., CapitalOne, Dominos, Honeywell), users can do number of things using voice commands helps us to improve the social life. These include so many applications like music, ordering pizzas, shopping online, scheduling an appointment, checking weather, making a payment, controlling smart devices. In order to help the users with usage convenience, many DVA devices like Amazon Echo, Google Home adopts an always-listening mechanism which takes input as voice commands all the time. The best part is that users need not press or hold a physical button on DVA devices before interaction with the devices. The device is programmed in such a way where it accepts voice commands no matter whether any persons are around the device. The sound pressure level (SPL) is considered and works for all the sounds is higher than 60dB. In third party voice services like Alexa-enabled smart device vendors there is no access control deployed at smart devices because they assume all the voice commands from the Alexa service are genuine and harmless. The successful work of Amazon Alexa is that it could work in omni-direction manner. This helps Amazon Alexa to listen in any direction in order to receive commands. The reasons why we consider Amazon Alexa are as follows. First, they are very popular and the bestselling flagship DVA devices. According to the reports, Alexa devices have been sold for over 5 million within two years since launch. Second, the Alexa provides services to their users with more than 10,000 skills (Alexa voice services) which are large scale than its competitors. DVA devices will help authenticate users by their voice biometrics before taking voice commands. But there are two complications that arise. First, voice of user's may vary with their ages, illness, or tiredness. Second, human voice is vulnerable to replay attacks. Some of the prior works are proposed to deploy wearable devices for user authentication. Solution is to force users to press a physical button for activating the Alexa devices before using it. With the help of the Amazon Alexa we are going to retrieve information about a student. . We can manage compute operation such as balance of memory, CPU, network, and other resources. The objective is to help faculty or parent to know about the particular student details.When parent or faculty asks about a student the Alexa replies for that particular query. This direct communication helps to improve time efficiency and cost efficiency for both faculty and parent. This is achieved through the Lambda function that we are going to used to develop the student information retrieval process.

2. MOTIVATION

In the DVA world, the do-it-yourself culture is encouraged, meaning IoT environments with tiny sensors and programmable brokers can be developed and customize devices and applications by users themselves. However, for people who are unfamiliar with state-of-the-art technologies to build customized IoT environments it is not that easy. Because of this factor most people tend to purchase IoT consumer products such as smart assistants, lights, sensors, switches, hubs, thermostats, and fitness devices. A variety of products are available on the market and we focused on one of the most famous products, Amazon Echo. The Amazon Echo family of smart devices also includes Dot and Tap, connect to the intelligent cloud-based voice service, Alexa Voice Service (AVS). With Alexa as a voice-activated personal assistant, the Echo is capable of doing various things, such as managing to-do lists, playing music, setting alarms, placing orders, searching information, and controlling other smart devices. Additionally, as announced at CES 2017, there is an interesting convergence of the Alexa with various devices, such as connected cars, smart fridges, and robots, which indicates that the Amazon Alexa-related environment will become an important source of information retrieval process. For these reasons, the Echo and Alexa were selected as the first targets for developing intuitive response system.

3. BACKGROUND: AMAZON ALEXA

In this section, we introduce Amazon Alexa devices and their common voice service model.

3.1 Alexa Devices:

Alexa devices can be categorized into three types namely, Amazon Echo, Amazon Tap and Echo Dot. , they connect to a cloud-based Amazon voice service in order to support voice commands. Amazon Echo was introduced as the first generation Alexa device. Alexa stays in a listening mode and it does not respond until it hears the command “Alexa” to wakes it up. It serves only one voice command and then returns to the listening mode whenever it wakes up. It appears as a 9.25-inch-tall cylinder speaker with a 7-piece microphone array. Amazon Tap is a smaller (6.2-inch-tall), portable device version with battery supply, but has similar functions. Echo Dot is the latest generation, which is a 1.6-inch-tall cylinder with one tiny speaker. Both the Echo Dot and the Amazon Echo, which require plug-in power supplies, are usually deployed at a fixed location (e.g., inside a room). In this work, we focus on the Echo Dot to examine the Alexa voice service

3.2 Alexa Voice Service Model

The Alexa voice service supports the recognition of voice commands to Alexa devices. Figure 1 illustrates how the voice service works with Alexa devices to control smart home devices (e.g., smart bulb, thermostat, etc.). To control a smart device, a user can speak a voice command to an Alexa device after waking it up with voice “Alexa”. The Alexa then sends the sounds of that voice command to a remote voice processing cloud via its connected WiFi network. Once the cloud recognizes the sounds as a valid command, it is forwarded to a server, called smart home skill adapter, which is maintained by Amazon to enable the cooperation with third-party service providers. Afterwards, that command is sent to another cloud which can control the corresponding smart device remotely.

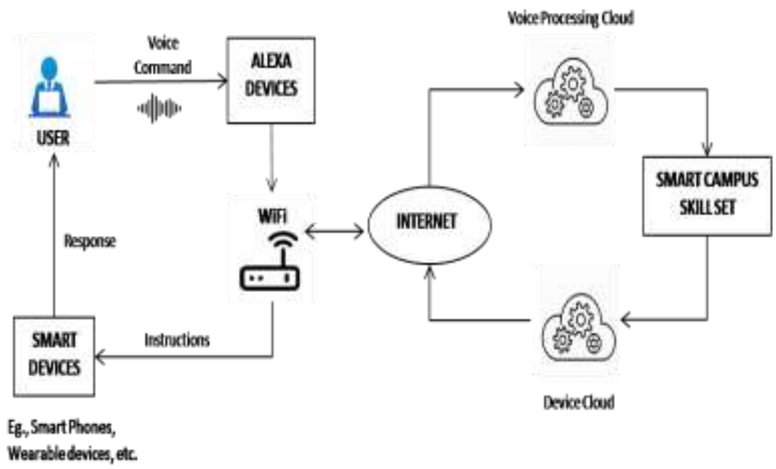

Fig-1: Alexa voice Service model

4. RELATED WORK

4.1 Alexa Voice Service:

Alexa Voice Service (AVS) is Amazon's suite of services built around its voice-controlled AI assistant for the home and other environments. Alexa is available for an ever-increasing number of other devices, including smart phones, tablets and remote controls.AVS is tightly integrated with Amazon's e-commerce environment, which means that it makes purchases fast and simple. The system can operate as a home automation hub, allowing the user to control heating and lighting systems and also customized query. Alexa also connects to streaming media services online, and supports If This Then That (IFTTT), an online service that automates Web-based tasks so that when user-specified events occur, follow-up tasks are triggered and handled. In the AVS environment, services are known as skills. Alexa Skills Kit, a software development kit (SDK), is made freely available to developers and skills are available for instant download from amazon.com.

4.2 Alexa Skill Kit:

The Alexa Skills Kit is a software development kit (SDK) that enables a developer to build skills, also called conversational applications, on the Amazon Alexa artificial intelligence assistant.The Alexa Skills Kit is comprised of tools, application program interfaces (APIs), code samples and documentation that enables a developer to add skills to the 10,000-plus voice recognition capabilities available on Alexa.Amazon Alexa is based in the Amazon Web Services (AWS) public cloud. A developer can upload Alexa skill code to AWS Lambda functions to execute code that is triggered by voice interactions. AWS automatically manages the compute resources for Lambda. A developer can certify, publish and update skills, which are made available through the Alexa Skills Store.An organization can build an Alexa skill to connect to end users via the conversational Amazon Echo platform. A developer programs the voice user interface to return a variety of voices, accents and responses based on the code for the skill.Custom skills allow the developer to define requests that the skill can handle, define the vocabulary required from the end user to make the skill request, and define the invocation name for Alexa to recognize the task. Custom skills are flexible and can handle several requests, but they require the most code to generate.A developer does not need to build a custom voice interaction model with smart home skills, but must create code to respond to a request. Flash briefing skills enable businesses to share pre-recorded audio content from feeds on Alexa with end users, such as news and weather updates.

5. LITERATURE REVIEW

Digital Voice Assistant (DVAs), also frequently referred to as Intelligent personal assistants (IPAs), virtual personal assistants, digital personal assistants, voice-controlled or conversational agents. Earlier handheld computers that were developed and designed to store information (e.g. contacts, calendars) and used to perform simple tasks (calculations, messaging).The current generation of DVAs includes Microsoft Cortana, Apple Siri, Google Assistant/Now, and Amazon Alexa. The DVAs are designed to accept user input from a touch screen virtual keyboard, handwritten or voice-controlled interfaces, answer user queries in a natural language and perform other tasks, such as play music, set calendar reminders and place online shopping orders. Alexa Voice Services is particular software designed to operate on the Amazon Echo, Amazon Dot, and related hardware. It performs voice-operated functions by communicating through a local Wi-Fi Internet connection with Amazon's AWS cloud servers, or other networked devices, to carry out these functions. In addition to obtaining data from Amazon's servers, the software can be used to control smart home devices, such as lighting and security systems. Alexa can be activated when its speech recognition software receives a word or phrase "Alexa" from a user which helps to activate the device, but this trigger word can also be customized by the user.

The Alexa hardware's has multiple microphones that utilize "far-field voice recognition" so that it can pick up speech patterns from any direction (omni-direction). But through the other noises Current Alexa voice-recognition technology cannot distinguish between multiple user voices, so a command or a user interaction can be easily interrupted. Whenever Alexa is voice-activated, the hosting device lights up, making the interactions primarily audible, with feedback available in the Alexa if the user chooses to access the information. Current DVAs differ in their UI designs, hardware requirements, and purpose of the task they are designed for. A recent comparison of DVAs suggests that Google Assistant performs better than other DVAs on travel, traffic, flight, and translation requests .Microsoft's Cortana excels in task reminders (e.g.chores, calendar, communications).

Strengths of Alexa includes support for the voice-activated purchases from Amazon's website and applications designed for specific types of tasks. Published studies on DVAs tend to focus on evaluation frameworks of this technology and factors related to user satisfaction, expectations and sociability. By testing the performance of Microsoft's Cortana on a Windows smart phone, Jiang et al. (2015) proposed a model of predicting user satisfaction from the action sequences in a session. For example, slower speaking rates and switching from voice to text input were found to signal dissatisfactory interactions. The authors suggest that while some of the satisfaction measures adopted from the previous web search studies might still apply to the DVAs (e.g. most of the click, request, and response features), acoustic, voice to- text or other newly designed features might be more appropriate for evaluating DVAs. Kiseleva et al. (2016) conducted a similar user study in order to develop an automatic method for predicting user satisfaction with DVAs using voice commands, physical touch gestures and other interaction signals. The authors concluded that incorporating touch-based features, such as scrolling or swiping, dramatically improves prediction quality of the user satisfaction model. In trying to understand everyday uses of the DVA, Luger and Sellen (2016) interviewed 14 participants about their usage patterns, motivations and expectations of the DVAs. The authors found that users' uncertainty about system features and abilities often lead to frustrating experiences and non-use. The study resulted in several recommendations for the DVA system design including revealing system intelligence levels to the users and improving system feedback. Several studies examined the DVAs uses in social settings. Porcheron et al. (2017) examined the case of Amazon Echo use in the social setting and found it to contribute to, among other things, the repetition of queries, lapses in conversation resulting from query submissions, body positioning to include the device, and collaborative query refinement. The authors note that the slower speed of interacting with the device, as compared to the pace of social interaction, may be problematic to the device's integration in the social setting.

Additional problems with the use of DVAs in social settings are discussed in Easwara and Vu (2015) who explored the social concerns around the use of the voice controlled assistants. The authors found that people tented to avoid using voice input in public settings due to privacy concerns. Similar findings were obtained in the study of the smart watch users, where the watch owners avoided using voice commands due to concerns for socially acceptable behaviour around strangers. However, we did not identify any reports of user interactions with the Amazon Alexa in the naturalistic setting. Most of the reported studies were conducted in an experimental setting on homogenous user groups. So, we decide to do develop our intuitive response system with the help of Amazon Alexa.

6. COMPARISION: INFORMATION RETRIEVAL ALGORITHMS

6.1Boolean retrieval Model

The Boolean retrieval model is the first model of information retrieval and the most criticised model. This model was introduced by George Boole. This model can be explained with the help of operators in George Boole's mathematical logic, query terms and their corresponding sets of documents can be combined to form new sets of documents. According to Boole there are three basic operators, the logical product called AND, the logical sum called OR and the logical difference called NOT. By combining terms with the AND operator we can define a document set that is smaller than or equal to the document sets of any of the single terms. For example, the query social AND economic will produce the set of documents that are indexed both with the term social and the term economic, i.e. the intersection of both sets. By combining terms with the OR operator we can define a document set that is bigger than or equal to the document sets of any of the single terms. So, the query social OR political will produce the set of documents that are indexed with either the term social or the term political, or both, i.e. the union of both sets. This is visualised in the Venn diagrams of Figure 2 in which each set of documents is visualised by a disc. In Figure 2, the retrieved sets are visualised by the shaded areas. The advantage of the Boolean model is that it gives expert system a sense of control over the other systems. If the resulting document set is either too small or too big, it is directly clear which operators will produce respectively a bigger or smaller set. For untrained users, the model has a number of clear disadvantages. Its main disadvantage is that it does not provide a ranking of retrieved documents. The model either retrieves a document or not, which might lead to the system making rather frustrating decisions. For instance, the query social AND worker AND union will of course not retrieve a document indexed with party, birthday and cake, but will likewise not retrieve a document indexed with social and worker that lacks the term union. Clearly, it is likely that the latter document is more useful than the former, but the model has no means to make the distinction.

6.2 Vector Space Model:

Gerard Salton and his colleagues suggested a model based on Luhn's similarity criterion that has a stronger theoretical motivation (Salton and McGill 1983). They considered the index representations and the query as vectors embedded in a high dimensional Euclidean space, where each term is assigned a separate dimension. The vector space model can best be characterized by its attempt to rank documents by the similarity between the query and each document. In the Vector Space Model (VSM), documents and query are represent as a Vector and the angle between the two vectors are computed using the similarity cosine function. Vector Space Model have been introduce term weight scheme known as if-idf weighting. These weights have a term frequency (tf) factor measuring the frequency of occurrence of the terms in the document or query texts and an inverse document frequency (idf) factor measuring the inverse of the number of documents that contain a query or document term . It is a simple model based on linear algebra and computes continuous degree of similarity between queries and documents. But still long documents are poorly represented because they have poor similarity values. Semantic sensitivity; documents with similar context but different term vocabulary won't be associated, resulting in a "false negative match".

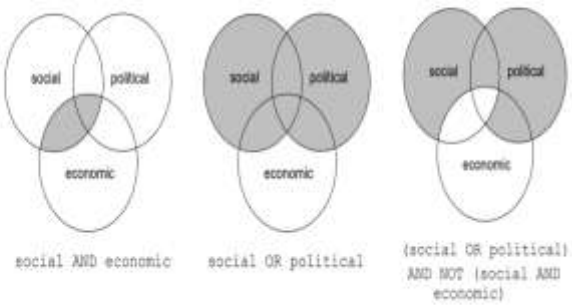

Fig-2: Boolean combinations of sets visualised as Venn diagrams

6.3 Probablistic Retrieval Model:

Maron and Kuhns introduced ranking by the probability of relevance, it was Stephen Robertson who turned the idea into a principle. He formulated the probability ranking principle, which he attributed to William Cooper, as follows (Robertson 1977).

“If a reference retrieval system’s response to each request is a ranking of the documents in the collections in order of decreasing probability of usefulness to the user who submitted the request, where the probabilities are estimated as accurately as possible on the basis of whatever data has been made available to the system for this purpose, then the overall effectiveness of the system to its users will be the best that is obtainable on the basis of that data”.

6.4 Inference Networks

The inference network retrieval model description we give here focuses on the details necessary to show how exact-match and vector space operations can be accommodated. In this model, retrieval is viewed as an evidential reasoning process in which multiple sources of evidence about document and query content are combined to estimate the probability that a given document matches a query. An inference network or causal network is a directed, acyclic dependency graph in which nodes represent propositional variables or constants, and edges represent dependence relations between propositions. If a proposition represented by a node p ' implies the proposition represented by node q. The node q contains a link matrix that specifies P(q\p) for all possible values of the two variables. When a node has multiple parents, the matrix specifies the dependence of that node on the set of parents (nq) and characterises the dependence relation- ship between that node and all nodes representing its potential causes. Given a set of prior probabilities for the roots of the DAG, these networks can be used to compute the probability or degree of belief associated with all remaining nodes. The inference network consists of two component networks: a document network and a query network. The document network represents the document collection and may incorporate numerous document representation schemes. The document network is built once for a given collection and its structure does not change during query processing. The query network consists of a single node which represents the user's information need, and one or more query representations which express that information need. A query network is built for each information need and is modified during query processing as existing queries are refined or new queries are added in an attempt to better characterise the information need. The document and query networks are joined by links between representation concepts and query concepts. All nodes in the inference network are binary-valued.

6.5Neural Networks

Recent advances in deep learning have seen neural networks being applied to all key parts of the modern IR pipeline, such as core ranking algorithms, click models, query auto completion, query suggestion, knowledge graphs, text similarity, entity retrieval, question answering, and dialogue systems. The fast pace of modern-day research has given rise to many different architectures and paradigms, such as auto-encoders, recursive networks, recurrent networks, convolutional networks, various embedding methods, deep reinforcement learning, and, more recently, generative adversarial networks, of which most have been applied to IR settings. Because of the modular structure complexity the information retrieval system can be divided into three different subsystems. There are administrator subsystem, indexation subsystem and user subsystem. The administrator subsystem guaranties the administration of the documents. Administrator determines the document base from the document set. Document base manager then provides the system representation of the documents. It also determines a suitable model for document storage and creates the system representation of the documents. Indexation subsystem solves two tasks. Firstly, the creation of an index and secondly, the creation of a query representation that is comparable with the document index. User subsystem processes user query and searches for relevant documents. Firstly, user puts a query. User subsystem processes this query and assigns a keyword to it. Then the indexation subsystem indexes the query, which is then compared with the document index. The administrator subsystem retrieves relevant documents and sends them to user according to this comparison. The user can use feedback, in which the user marks the most relevant documents from the set of retrieved documents and consequently sends it as a new query. The system creates a new query from these documents and searches again the document base. These three subsystems of the information retrieval system can be represented as a three layer model. The first sublayer of this system is a query sublayer, the second one is the keyword sublayer and the third one is the document sublayer. The user enters a query, which is associated with a keyword, according to which the relevant documents are retrieved from the document sublayer. Transition of the information from query sublayer into keyword sublayer and transition of information from keyword sublayer to document sublayer can be replaced by neural networks.

7. COMPARISON OF VARIOUS INFORMATION RETRIEVAL SCHEMES

Table 1: Comparision of various algorithms

Paper Title	Author	Concept	Advantage
Ontology-based Digital Photo Annotation Using Multi-source Information	Yanmei Chai,et al	To overcome the difficulties of Users who encounter severe difficulties with the management and retrieval of information, especially when they want to find a desired one among tens of thousands of photos using just a simple query.	It provides manual annotation by automatically extracting semantic concepts from text, EXIF metadata and face detection result. It improves the performance of annotation by allowing users to freely edit the annotation information
Research and Implementation of Automatic Question Answering System based on Ontology	Xingbo Xie, et al	To implement the automatic question answering system. After fusing Ontology into the automatic question-answering, the system notonly can analyze the user's questions in the semantic level but also combine with the user's questions for semantic reasoning. Therefore, the users can get a better understanding an more accurate result.	Ontology has a good concept hierarchy and supports logical reasoning. It is better in reflecting the logical and hierarchical relationships between knowledge than ordinary database. This system is not only able to answer user's questions but also can provide relevant recommendations, which can help students study systematically.
Document Retrieval Using Knowledge-Based Fuzzy Information Retrieval Techniques	Shyi-Ming Chen, et al	The knowledge is represented by a concept matrix, where the elements in a concept represent relevant values between concepts.	Efficient retrieving capability and flexible user's queries are consequently provided. This system has implemented a fuzzy information retrieval system called MASTER based on the proposed method using Turbo C version 2.0 on a PC/AT.
Resource Discovery and Intelligent Image Retrieval in a Distributed system	Sudha Ram, et al	It proposes an intelligent agent based mechanism to locate the appropriate sources of satellite data, processing algorithms, and ancillary data that may be required at various levels of Processing to answer different types of temporal and spatial queries	This approach makes the system Scalable. It allows users to pose high level queries and relieves the user from the burden of deciding which resources to access, how to access them, and how to process the data.
Document Storage and Retrieval in a Neural Database	P. Parodi, et al	It is mainly a document database, collecting papers on the leech nervous system, which is maintained in a largely automatic fashion.	This method is accurate and fast. It deals successfully with documents.with an arbitrary layout, documents where graphical features are added.
Web Mining: A Key Enabler in E-Business	Nivedita Roy, et al	In this paper, it has been shown how web mining is integrated to the knowledge discovery process, its potential applications, and Techniques. An integrated architecture has been presented showing b how web contribute to e-business via the new technologies.	This technology helps in gaining Meaningful insights related to the day-to-day business activities by using the useful information made accessible through the web. It not only enables discovery of information from mounds of data on relevant the WWW, but it also monitors and predicts user visit habits.
OntoWrap-Extracting Data Records from Search Engine Results Pages Using Ontological Technique	Jer Lang Hong, et al	Ontological technique using existing lexical database for English (WordNet) for the extraction of data records. We find that wrappers designed based on ontological technique are able to reduce the number of potential data regions to be extracted, thus they are able to improve the data extraction accuracy.	Ontological technique could extract data records effectively. It is robust in its performance. This is an advantage as the list of potential data regions for extraction of relevant data region is significantly reduce and enhances the extraction accuracy.
Movie Related Information Retrieval Using Ontology Based Semantic Search	R.Suganyakala, et al	A query interface which requires the user to enter the query in natural language is provided. A domain- specific ontology based on movies is used to develop a prototype of the proposed model which improves search accuracy.	This ontology based search model improves search accuracy. User need not have a prior knowledge of ontology based query language which is very complex. This kind of interface tends to improve the usability of the retrieval system

8. CONCLUSION AND FUTURE WORK

DVAs enable users to control smart devices and get living assistance using voice commands. In this work, we have viewed different information retrieval algorithms that might help to develop a Alexa response system that can be used for smart campus. Also that we have compared different papers about the information retrieval systems and the advantages are listed. We hope Neural Network Information retrieval system will be best suited for our response system. We believe that our idea help parents and faculty to get information about the student in a very quick manner. In future work we can enable Alexa skill to work on other smart campus project that responds for other information such as behavioural activity and character of a student.

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