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Model for Smart Web services using Intelligent Assistance

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Abstract: *In current era of digitization most of the services are now offered as E-services; E- shopping, E Governance, E-Healthcare. For a non E-educated person it is the biggest challenge to survive in E-world. There is a huge gap between demand and supply of E-services. The world of internet is full of latest and advance web services but they are not being used by even 50% of total internet users. One of the reason for such a huge gap in; services offered and their utilization by common men, is lack of knowledge and fear. With studies it is found that corrective measures are required to deal with the problem. The work here is a sincere effort in the direction of providing smart web services for users. The work is an intelligent web service model using intelligent services. This paper focuses on the working of virtual assistant, a basic conversational User Interface that helps navigate the user through a website and provides help and answer. It is a basic Customer Care service or a friend that interacts with you like a personal assistant would. It is simple to operate, powerful and very intuitive. Such conversational bots have incorporated real-time learning and evolutionary algorithms, instead of just pattern-matching, thus moving towards being truly "intelligent".*
Keywords:*Chatbot, deep learning, customer service, intelligent system, conversational agent*

I. Introduction

A. Conversational Agents

Conversational Agents or Chatbots are all the rage today. They can simulate conversation and talk to both users and services using voice or text. There have been considerable advances in the field of Artificial Intelligence combined with interactions using natural language, including tech giants' core products like Amazon Alexa, IBM Watson, Apple Siri and a myriad of other intelligent personal assistants. Customer Care service is a critical feature of most businesses. It is a deal breaker for a customer if the help feature and assistance is not proper and cannot understand what the customer is trying to say. Besides being innovative, it should be robust and understand what the customer wants to convey and needs help with, and respond accordingly.

There are a myriad of chatbots powered by techniques like information retrieval and template rules. [1]Deep learning techniques have been applied to natural language generation and processing. Prior work on this focuses on general applications instead of specific contexts [2]. Users may ask questions seeking help with using a website or informational questions, like the ones presented in the FAQ section.

In this work, we create an Intelligent Assistant, a conversational User Interface that helps the user in this regard. It acts as a customer service "help desk" of sorts. A virtual assistant to help the user with his/her queries for navigating and smooth functioning and use of the website. A query system or QA (Question/Answer) agent of sorts to answer questions the user might have and poses about using the website or web application it is deployed in. It has a fun, user-friendly and intuitive interface to act as virtual customer support.

State of the art techniques in deep learning, like the Long short- term memory (LSTM) networks are first applied to generate responses to customer-service requests. The intelligent system takes the query as input, feeds its vector representation to the LSTM and finally, generates the response.

B. User Satisfaction

Many conversational agents (CA's) are developed to answer users' questions in a specialized field. They are built for the satisfaction of informational needs of the users, besides playful interactions for users' enjoyment. User satisfaction levels, areas of interest in conversational interactions, user status (for instance, a decline in user engagement) and user satisfaction (e.g. user's frustration, say the user says "shut up") etc. can be gleaned with each interaction. (For example, by recognizing signals and using association rules in underlying computational models). This information can be used to build user profiles and conversational agents can be made to adapt functionality and interaction styles based on the users' conversational behaviors and needs.

The signals, found using static modelling, enable real time adaption to algorithms and system functions according to user status and satisfaction. We discuss the direction of development of these adaptive conversational agents [5] and their design implications, in the domain of customer service. Adaptive Agents are particularly interesting to Embodied Conversational Agents (ECA) and Human Computer Interaction (HCI) communities[6,7].For instance, by recognizing signals in users' behavior like gaze fixation[8] and attentive replies (like "un-huh")[9], which are signs of user engagement, we can infer user status. In case of decline in user engagement, adaptive agents can employ techniques to increase it. Customer Care chatbot is built in its own platform, thereby more useful and faster. It is built using Botpress API into a Customer Support Conversational bot and deployed on a website. Botpress is an open source Bot framework that helps us create and reuse open source modules for bot creation.

II. Conversations With Conversational Agents

CAs has been developed for as long back as 1950's. A prominent example is ELIZA [10].Within the field of Human Computer Interaction, the research focus was on embodied CA's. Anthropomorphism is emphasized in regulation of human computer interactions in a familiar way and manifesting social intelligence, for e.g., trustworthiness [11, 12]. However, chatbot is a term attributed to CA's that employ text-based or speech-based input without the embodied element. These are mainstream chatbots, where the focus is not on anthropomorphism [13], but on task performance, since these are a part of core utility applications. Customer Service is one of them [14]. However, human conversations are still complex machinery in their own right [15].

Most CAs, besides instrumental usage (like customer service) includes capabilities for lifelike conversations i.e. playful interactions (like human and humorous responses) (unrelated to help and support [20, 21, 22].Some users prefer these human responses and fun conversations [23] and others prefer only pertinent information [24]. This leader to differences in how users evaluate the bot. Thus, agents also attribute these lifelike qualities.

Thus, it is necessary to study the pattern of conversational interactions with CAs i.e. user utterances in performing communicative and social functions instead of task-oriented functions. Early systems avoided unbounded conversations initiated by users (e.g. [16]). But this approach is inadequate for realistic conversations which are not agent-controlled and it is obsolete for free-form conversations, such as those by Question Answer Agents, like the Customer Support Agent. The anticipation of user responses, for instance using a rule-based system, and adequate system knowledge, to avoid responses like "Sorry, I don't get it" on the agent's part, is necessary and what makes our bot "intelligent". The agent needs to bootstrap from the user data [17]. There is a domain independent pattern in conversations that is studied. A few qualitative studies [18, 19] give an empirical study of user interaction patterns.

III. Techniques Involving Deep Learning

The conversation between the user and the bot can be viewed as mapping the user input to the output response. This mapping from sequences to sequences can be achieved and learnt using deep learning techniques. This chatbot basically uses a novel integrated approach of two (machine/deep learning) methods- Information Retrieval (IR) and Sequence to Sequence (Seq2Seq).

A Q/A query base were developed from the customer's log and FAQs in the company's database as input to the chatbot engine. Questions and Answers were paired up and if the responses fell under the designated threshold, then the IR method was used, otherwise the sequence model was followed. The sequence model was expressed in a defined probability range of words. Thereafter, three implementations were chosen to develop the sequence model- Bucketing and Padding (in Tensor Flow),Softmax Regression and Beam Search. A sequence model was developed using a user's query or word pattern using a standard formula. The approaches were then integrated and used.

- Sequence to Sequence Learning [3] - The core consists of two LSTM networks- an encoder that maps an input sequence of variable length to a vector of fixed length, and a decoder, that maps the vector to an output sequence of variable length. (Sequence to sequence based chatbot engine).
- Word Embedding method, word2vec neural network language model [4] is used to learn distributed representations of words from customer care conversations in an unsupervised way. Each dimension of the embedding represents a latent feature of a word, capturing its syntactic and semantic properties.
- Information Retrieval-used to retrieve information using deep learning by training neural networks to fetch appropriate responses using information retrieved from input data?

IV. Building The Bot

A. Major Components of a BotPress Bot

We train and customize our bot for Customer Support, Help and FAQ's by using the following features of BotPress.

- Modules are components outside of the Bot Core that are used to add features to the bot. They are reusable pieces of code that can be used to build the bot.

They are of three types: Channels, Skills and Functional. Channel is a module that allows our bot to send and receive messages from already available chat platforms like Facebook Messenger, Telegram, etc.

- NLU (Natural Language Understanding) is a subset of NLP that is used to convert the unstructured messages in a structured form that the Bot can use. It replaces the obsolete keyword detection technology. It is complex and involves linguistics and machine learning. However, there are abstractions like Dialog Flow (Google) and IBM Watson available. We install botpress-nlu module to use it
- Dialog Manager is used to decide what the Bot would respond to messages by the user. We could manually implement it using if-else statements but that is complex, given the unpredictability of user queries and natural language. Botpress combines the Visual Flow Editor with Dialog Manager to abstract that complexity.
- Content Elements are structured objects which hold the information (response) to be contained and Content Renderers are functions that render and display that information or message in a platform-specific way.
- Content Types are domain specific to the bot and group similar content elements together. Developers define it specific to the bot being created. For example, for this bot, we create “Questions with choices”, “FAQ’s” etc. for customer support. Each content type is created in JavaScript and is its own .form.js file. Botpress automatically finds and registers content types based on directory and naming conventions of the file.
- Flows specify our conversational logic. Complex conversations are broken down into smaller flows. They are stored in JSON files in the Bot Source Files.
- All conversational logic is defined in “nodes”.
- Each conversation has a “state” assigned to it, for instance, the starting and ending of a chat session
- Actions are functions executed on the server side as a part of conversational flow to perform tasks like alter the state of the conversation, send customized messages and execute code to run API’s or store data in a database.
- BotPress provides its own data storage mechanisms to handle data storage for us, e.g. Storing data in the state itself or storing user- specific data using User Tags or using a built-in database (like SQLlite).
- Skills are high level abstractions of flows i.e. dynamic flow generators that store flows where we see common patterns. They are included as a module- @botpress/skill

B. The Website and Deployment

We can give our bot attributes in the .js file, for example:

```
constwebchat
= {
        botName: 'Customer Care',
        botAvatarUrl: null, // You can provide a URL here
        botConvoTitle: 'Botpress Basic Customer Care Bot',
        botConvoDescription: "Hello,May I Help you!",
        backgroundColor: '#ffffff',
        textColorOnBackground: '#666666',
        foregroundColor: '#000000',
        textColorOnForeground: '#ffffff'
          };
```

We could respond to events, i.e. messages from the user, say greetings such as ‘hello’, as in the following code snippet.

```
bp.hear({
        type: 'message',// type of event
        text: 'hello'
      }, (event, next) => {
     const id = event.user.id
     const text = ‘Hey, how may I help you?’
     bp.messenger.sendText(id, text)
      })
```

Similarly, we train the bot to respond to various user messages by specifying event handlers.

Botpress web supports a variety of message types that can be rendered by the bot. We can implement our own custom types also. We use a botpress module called Webchat-extension. In thebotpress section of the json file, we mark it as a webchat-plugin via isPlugin flag.

```
{
        “botpress”: {
                “webBundle”: “bin/web.bundle.js”,
                “noInterface”: true,
                “isPlugin”: true,
        “plugins”: [{“entry” : ”Entry”, “position”: “overlay”}]
}
}
```

We deploy our Bot and embed script from the bot to our website as below.

```
<script>
        window.botpressWebChat.init({host: ‘<url>’ })
</script>
```

Our bot is now ready and available and helps the user navigate our website.

V. Evaluaiton Of The Bot

A content analysis was conducted to identify the types of queries the user makes and how the system responds to them. A similarity measure between the expected response and the generated response was established. The response generated was measured by a human metric and an automatic evaluation metric.

- Content Analysis- The requests made by the user were sampled and categorized into intents. The bot was trained with dialogues and responses appropriate to the categories, which were assigned to example conversations and aggregated.
- Human Metric- The bot’s performance was tested by humans, based on three rating criteria- appropriateness (if the response was of the same category as the request and made sense), empathy (if the bot sounded polite and helpful and made the customer/ user feel valued) and helpfulness (useful and concrete advice that actually assisted the user and solved his/her problem/query). A survey task was undertaken and participants were asked to rate the quality of the bot’s response based on the above criteria.
- Automatic Metric was established to rate the response time and quality of the bot based on a few sample conversations the bot was trained with.
- Deployment and Survey for User Satisfaction- the Bot was deployed and tested by some customers and users of the website, mostly college students, to capture user satisfaction and rate the bot’s responses. The user satisfaction was measured using four criteria- Understanding (if the bot understood the question), Relevance (if the information presented was relevant) and Quality of the answers provided and Sociability (if the bot was friendly and fun).
- The results were that the bot was used a lot during early deployment and user questions ranged from greetings and common communicational utterances like “hey”, “ok” to off topic conversations (“tell me a joke”) to feedback about the agent (“thanks”, “good”, “shut up”) and help topic questions (“how do I register?”). One-third of the questions were small-talk related[25] and some patterns that are not observed in human conversations, for instance, testing of the bot’s intelligence by asking unreasonable questions, were observed.

VI. Limitations

Although, our customer service and support bot was able to answer basic help FAQs, it couldn’t capture all the nuances of human conversation. It did not cater to some rarer form of user comments. It cannot answer everything under the Sun, but did cover some basic help topics that the user needs to navigate the website. It can also be made more interactive and interesting for the user, with better design and voice interface. It could be more “human” like in some respects, i.e. the flow of conversation resembling human conversations.

VII. Discussions And Future Work

We observed that the deep/machine learning based intelligent system was able to learn writing styles and user query styles and generate appropriate and relevant responses that helped the user. Future work can explore supervised learning techniques to train the bot using filtered training data with certain styles and categories of conversations, so it can generate output sentences using specified styles. Our Bot is maintained

using the inbuilt version control of BotPress. We customize and modify it as per changing needs using the BotPress dashboard. Our next step is including a Voice Interface, besides text as a conversation medium. This makes it more users friendly and caters to a wider user base, some of whom may not be comfortable with a text-based UI.
This chatbot is designed to be more of a "friend" than a typical machine interface.

Chatbots in customer service is another application of intelligent systems and deep/ machine learning that open new avenues for interaction between static/dynamic sites and users, which helps user to navigate the site better and make the most of it, thereby exploring stuff that they would not have been able to on their own as easily and conveniently. It encourages interaction between the user and the brand/ company (whose website they are using) and increases customer satisfaction and convenience, while providing an innovative, responsive, easy-to-use and fun User Interface, making the user want to use the site more and more, thereby also helping the brand image. (and increasing advertising revenue).

In the late 2015, the field of chatbots or talkbots- a conversing robot or program and their development, was much commonly discussed among data scientists. The reason was a foray into the area of addressing user queries intelligently (and automating that/automatically) besides making regular, casual conversations that occur on a daily basis among humans. They may not replace the human aspect/element completely yet, but do make our lives better and cuts down on organizational costs (the costs incurred in hiring humans for the same).

Chatbots can bring a positive impact in the rapidly changing technology ecology. It can profilerate automation and make stuff easier, reduce the need for human capital and save human time and energy, which could be put to better use. It will also increase convenience and shoot up profits in various sectors, like the customer service sector. On the other hand, it could be misused if it falls in the wrong hands. (Moreover, there is a risk of humans in the same field losing their employment. That, however, is remedied by creation of new, different jobs involving/employing/engaging human creativity, innovation and intellect and reskilling the work force for them.) Same is the case with any intelligent system or largely, Artificial Intelligence as a field. For example, in June 2017, Facebook's chatbots developed their own language to communicate with each other, baffling the employees.

Although, research on conversational agents has come a long way in the past half century, there are two criticisms that prevail. One is the gap between their working in the lab and on the field and a lack of understanding on real life user experience. Second is the restriction of conversations to specific domains and despite the availability of intelligent personal assistants that encourage the user to ask them anything, very less information is available on user interests. This poses a challenge for the development of conversational agents, which relies heavily on an anticipation of what the user might say instead of concrete information and adaptation based on user needs. There is a tradition of separating social dialogue i.e. communicate interaction and task-oriented interactions. The former is more unrestrained and therefore, complex to anticipate, but it is generalizable across domains, therefore, there is also focus on building domain-independent conversation architectures to make the development of CAs easier and more efficient.

The results and use of Customer Service bot provide an understanding on the underlying functions of conversational behaviors with conversational agents and chatbots and their deviations from human conversations. This basic chatbot may help the design of more complex CAs and contribute to the emerging fields of conversational User Experience and Interface.

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