I.J. Information Engineering and Electronic Business, **2023, 2, 1-10**
Published Online on April 8, 2023 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijieeb.2023.02.01

Developing Smart Conversation Agent ECOM-BOT for Ecommerce Applications using Deep Learning and Pattern Matching

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Received: 02 November, 2022; Revised: 24 December, 2022; Accepted: 02 February, 2023; Published: 08 April, 2023

Abstract: Chatbots are a technological leap in conversational services, generating messages to users either following a set of rules to respond based on recognized patterns or training themselves from previous data or conversations. The primary goal is to enable a device to communicate with a user upon receiving natural language user requests using artificial intelligence and machine learning to generate automated responses. Technology is progressively catering to the questions, both in academic and business contexts, such as situations that require agents to investigate the cause of customer dissatisfaction or to recommend products and services. Significance of this research is to reduce the human dependency and improving customer support by providing close to human natural responses using pattern matching and deep learning on the custom-made data. The main objective of this work is to (a) study the existing literature on cutting-edge technologies in chatbot development in terms of research trends, legacy components, techniques, datasets, and domains specifically in e-commerce and (b) to develop a product that fill some of the gaps/missing functionality identified in current frameworks. We have achieved the following, (a) generated small yet generic dataset, which can be used for all types of products, (b) the intents are identified accurately by the bot using deep learning, whenever a user query.

Index Terms: Chatbot, Ecommerce, Pattern matching, Machine learning, Natural dialog interfaces, Natural language processing, Deep Learning.

1. Introduction

Artificial intelligence (AI) has changed how we perform our daily activities by developing and evaluating advanced applications and devices called intelligent agents that can perform many functions. Chatbots can be classified as AI programs and human-computer interaction (HCI) models [2]. They use natural language processing (NLP) and emotional analysis of oral communication between people using written or spoken language and humans or other chatbots [3]. Communicating objects such as interactive agents, intelligent robots, and digital assistants are also called chatbots. Besides modeling human-entertainment interactions, chatbots can be applied in many other fields such as education, business and e-commerce, health, and entertainment [4].

Performance is the most decisive driver for chatbot users, besides entertainment, social, and interactive elements with new products. Also, chatbots have become very popular among businesses as they can serve multiple customers while reducing service costs. Chatbots are more user-friendly and engaging than searching for static content in frequently asked questions (FAQs) lists. It provides convenient and efficient support when communicating with users. They answer the question directly by providing more interesting answers [5, 6]. Users see chatbots as friendly companions rather than mere helpers [7].

The degree of trust in a chatbot depends on points regarding behaviour and appearance and other providers, privacy, and security issues [9]. The development of this trust relationship depends on how human-like the chatbot is, which, in turn, depends on its visual characteristics, how close the name is to humans, its personality, and its effectiveness with human language [10]. Emotions are another essential part of humanizing chatbots, and there are many ways to create emotion-aware chatbots [11]. Advances in artificial intelligence are expanding the ability of chatbots to mimic human agents in conversations.

Generally, the product information is given, or the product selling is done by having a conversation with customer service agents online which involves human intervention for answering queries related to Product Name, Category, Color, and other common fields. The primary purpose of this project is to enable and facilitate users i.e., the sellers through a chatbot in the process of having an intelligent conversation with the buyer without human intervention. The chatbot communicates in a way that it analyzes every query to understand intent in the statement and responds according to the query which seems closer to human like conversation. Also, the system maintains the history of conversation and extracts the necessary information from the text to search out the queried product in a database or to give order details queried by the customer. This greatly reduces the manual work done by the user and enhances the user experience.

This research work analyses the state-of-the-art Chatbots, challenges, and how researchers/companies handle them. The focus is on the e-commerce domain by analysing the needs of e-commerce stores and creating a chatbot to meet their needs. During the pre-processing stage, the developed algorithm employs word lemmatization, tokenization, and sentence segmentation. Once the training is done, the algorithm does sentence segmentation for recognizing products and attributes after the transcription is complete.

Sentence segmentation or chunking is accomplished with the NLTK POS tags and tokenization. The trained model aids a user to spot the intent to find the used words and quickly perceives the prominent terms to determine their importance. The final product of this work is a GUI interface in which the user input a message and the Bot responds accordingly. Then the messages and intent logs are maintained to investigate the previous chat of the user to find out the products and orders in a csv file will be transcribed. The next stage is to perform text analysis on the transcribed text.

In this work, Python has been used to build contextual assistants with the support of training examples to train the chatbot on how to respond in certain situations. The chatbot understands the intent(s) of the human accurately using neural networks about what they are looking for and then answers their questions intelligently through REGEX by engaging the user in the conversation. The following functions of e-commerce businesses are addressed in this project:

- Buying and selling
- Product Information retrieval
- Order Tracking
- Refund

The rest of the paper is organized as follows. In Section 2, the literature review is presented. In Section 3, the approach including the architecture of chatbot is presented. The project implementation details are discussed in Section 4, Section show the conversations in a form of results obtained from chatbot. Finally, Section 5 consists of a conclusion.

2. Literature Review

This chapter describes the historical evolution of chatbots from the beginning of their creation till 2020 along with their classification. The main difference between human-to-chatbot communication is content and quality versus human-to-human conversations. Conversations between humans and chatbots are long driven, while people often use short vocabulary, poor vocabulary, and even slang. A more significant difference between chatbots and humans is how empathy is perceived, as chatbots are less likely to understand conversations than humans. The section below provides a quick summary of the evolution of chatbots in the last six decades.

2.1 Chatbot Chronicles

- In 1966, ELIZA, a psychotherapist's chatbot that returns the user's sentences in question form.
- PARRY appeared in 1972. He Behaved Like a Schizophrenic
- Jabberwacky, written in CleverScript in 1988, was a spreadsheet-based language that facilitated chatbot development and responded using contextual pattern matching based on previous discussions.
- In 1991, it was a real-time multiplayer virtual world (TINYMUD), an artificial player whose main function was communication. Many real human gamers seem to prefer talking to Chatterbot.
- In 1992, Dr. Sound Blaster AI Text-to-Speech Operator (Sbaitso), Dr. sound cards could produce sound. He acted as a psychologist without complex interactions.
- In 1995, the first online chatbot inspired by ELIZA, ALICE (Internet (Wallace, 2009) ALICE was based on pattern matching.
- In 2001, SmarterChild marked a true evolution of chatbot technology that was available on messengers such as America Online (AOL) and Microsoft
- Siri, developed by Apple in 2010, paved the way for personal assistants
- In 2011 IBM created a chatbot called Watson (Watson Assistant | IBM Cloud, 2020)
- Google Now in 2012 (Google Now, 2020) was originally used to provide information to users based on time, location, and preferences.
- In 2014, Microsoft developed the personal assistant Cortana (Personal Digital Assistant - Cortana Home Assistant - Microsoft, 2019). In the same year, Amazon released the Alexa.
- In 2016, Google Assistant was developed, representing the next generation of Google Now (Google Assistant, your Personal Google, 2019).

2.2 Categories of Chatbot

Chatbots can be classified into informational, chat-based/conversational, and task-based. Informative chatbots are used when users interact with a chatbot to retrieve specific information stored in a fixed source. In chat/conversation-based chatbots, a natural conversation is expected with users, whereas task-based chatbots perform various functions, such as booking a room and doing a great job of requesting information from the user and responding appropriately.

2.2.1 Task-Oriented Dialogue System

It consists of manual rules that guide users to achieve a specific goal or complete a specific task in a specific area [21], such as booking, traveling, buying, or ordering food. Examples of such systems include Apple Siri, Microsoft Cortana, Facebook Messenger, and Google [21]. There are two approaches to developing task-oriented systems: the supervised approach and the unsupervised approach.

2.2.1.1 Supervised Approach

It employs manual feature extraction and annotated datasets like user input parsing models into a semantic representation. The limitations of the supervised approach, such as manual data annotation and feature extraction, lead to high costs and low scalability [21].

2.2.1.2 Unsupervised Approach

This approach automatically learns features from unlabeled datasets. Deep learning approaches trained on neural networks, such as CNN (Convolution Neural Networks), 6 capture the interactions between messages and responses. Another endpoint-oriented dialog system uses the Wizard-of-Oz pipeline structure to collect designed dialogs and dialog sets without manual functionality [21].

2.2.2 Non-task-Oriented Dialogue System

A non-task-oriented dialogue system works in various fields, such as games, chatter, or entertainment, without assisting the user performing any task on a particular task. ELISA and PARRY fall into this category. This approach allows chatbots to learn from a large number of conversations available on social networks or the internet. The employed methods are either lookup or generation-based [21].

2.2.2.1 Retrieval-Based Chatbot

These dialogue systems have a knowledge base with a large number of question-and-answer pairs based on statistical linguistic models for appropriate answer selection. They are based on a vector space model that uses a degree of similarity between the message and the response for selecting the correct answer to user input. This is achieved through various text similarity features, including subject similarity, cosine similarity, and translation score. Another approach used is a linear network for efficient communication. For e-business, chatbots are designed to provide instant answers to frequently asked questions (FAQs) from customers. It is often used as [21] a combination of artificial intelligence markup language (AIML) for answering common questions and latent semantic analysis (LSA) for answering questions.

2.2.2.2 Generation-Based Chatbot

Statistical machine translation and sequence-to-sequence (S2S) platforms have been developed [21] to generate responses to user input that use neural networks to encode messages and other recurrent neural networks with attention mechanisms to generate responses. This can be more useful as it produces a generic response. There are also hybrid generative algorithms that combine Finite State Machine (FSM) grammars with a corpus language model.

3. Methodology

This section describes the development and the critical issues other than the architectural design relating to the developed e-commerce bot, Ecom-bot. There are primarily two approaches to developing a chatbot: (a) pattern matching and (b) machine learning.

3.1 Pattern Matching

A rule-based chatbot matches user input with a pattern of rules and uses a pattern matching algorithm to choose a predefined response from a set or list of responses. Context can affect rule selection and response format. The three most popular languages for implementing chatbots with a pattern matching approach are Artificial Intelligence Markup Language (AIML), RiveScript, and the Chat script.

3.2 Machine Learning

In this approach, chatbots use natural language processing (NLP) to extract content from user input and remove the ability to learn from conversations. The approaches in this category involve NLP, NLU, Machine Learning, Deep Learning model. Chatbots can be developed using programming languages such as Java and Python or using commercial or open source chatbot development platforms.

3.3 Proposed Approach

The proposed Ecom-bot employs a dialog corpus and a deep learning model using the Bag of Words (BOW). The corpora consist of generic statements which do not have any specific entity and contain patterns in a sentence to classify between intents like searching or placing an order. Thus, a combination of rule base and self-learning is used. For the self-learning part, neural networks are used to train the chatbots to respond to a user based on training interactions. For rule base, rules for POS tags have been created for sentence segmentation.

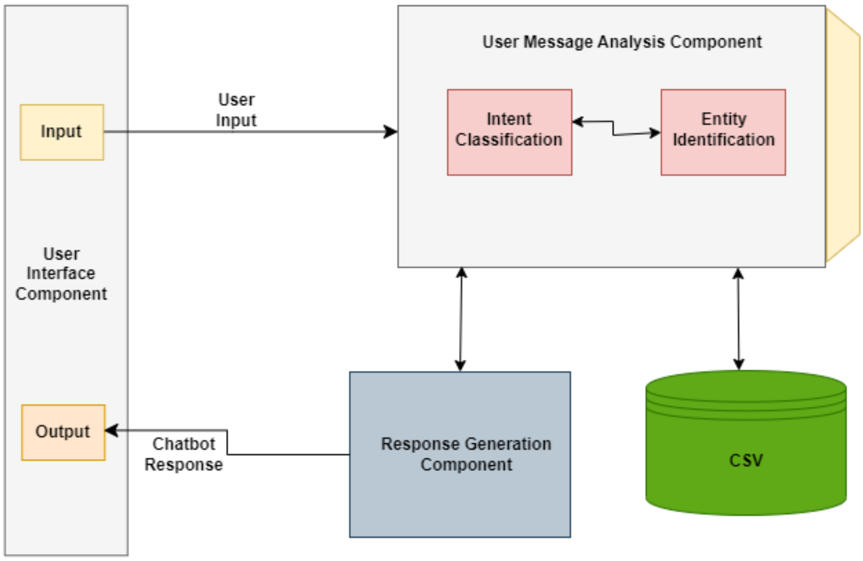

Fig. 1. Ecom-bot Chatbot Architecture

The chatbot for this work, Ecom-bot, is built using Python and employs many NLP libraries in addition to training a neural network. The GUI is developed using the Tk interface in Python. Fig 1 shows the architecture of the designed chatbot.

3.4 Workflow

There are 2 main modules of the chatbot the training module and Interface which can be considered as a testing module where the conversation takes place.

3.4.1 Deep Learning for Training

In the training module there are intents defined in a JSON file structure where each intent consists of a tag, template, response, and context. To add novelty to the approach we created generic patterns in intent file so that the number of intents in the file does not increase and the file does not clutter. This approach allowed to create generic intents and encode the user message on other end i.e., GUI according to the template to test it on multiple products to make it work dynamically. For example, for product search, one of pattern is “I am looking for Product” and whenever user enters “I am looking for bag” the keyword ‘bag’ is replaced with the ‘product’ to make it compatible with patterns in our intents file. This way it allowed us to use the same pattern for multiple products instead of writing same kind of patterns for different keywords. It helped in increasing our accuracy of our model as there were scenarios when the model couldn’t predict the correct pattern due to change in product name as it couldn’t recognize it. Also, it reduced the training time for model on lesser number of intents. Fig 2 contains the intents based on the possible patterns user could ask or input about the product purchase and search. Tags are assigned based on the intent for the bot to classify intent and generate responses.

```
File Edit Format View Help
        "responses": ["Please provide your email for more clarity?"],
        "context": ["order_id_input"]
       },
       {"tag": "search",
        "patterns": ["I want to search for product", "I am looking for product", "Load result for", "Show results for me", "Find me " ],
        "responses": ["Please specify the gender you are looking for "],
        "context": ["search_shoes"]
       },
       {"tag": "search_product_by_gender_category",
        "patterns": ["I want to search for product for gender","I am looking for product for gender","I am searching for product for gender", "I want to buy
        "responses": ["what category are you looking for i.e.?", "which "],
        "context": ["search_shoes_by_gender"]
       },
       {"tag": "search_by_product_category",
        "patterns": ["Find me product category", "Find product category", "looking for product category", "I am looking for product category"],
        "responses": ["Sure would you like to give more details? like what gender? females/males/boys/girls/kids"],
        "context": ["search_shoes_by_category"]
       },
       {"tag": "product_category",
        "patterns": ["product category"],
        "responses": ["Sure would you like to give more details? like what size are you looking for"],
        "context": ["shoe_category"]
       },
       {"tag": "gender_category",
        "patterns": ["gender"],
        "responses": ["Sure would you like to give more details? like what size are you looking for"],
        "context": ["gender_category"]
       },
       {"tag": "search_by_product_category_gender",
        "patterns": ["Find me product category for gender", "Find product category for gender", "looking for product category for gender", "I want product c
        "responses": ["Sure would you like to give more details? like what size are you looking for"],
        "context": ["search_by_product_category_gender"]
       },
       {"tag": "search_by_product_category_size",
```


Fig. 2. Intents.json

Once the intents file is created the dialog corpora is trained on a deep learning model using the Bag of Words (BOW). The data preprocessing takes place in this phase where each pattern in intents file is first tokenized using nltk tokenizer. Each word in each pattern is tokenized and stored in a word list. Simultaneously a class list is maintained using tags in intents that maps a class to a corresponding token. Also, another document list that carries both the token and its class at the same place is constructed. The document and the word lists are then lemmatized using nltk lemmatizer and the words are converted to lower case. Then a bag list is created which has 1 if word is there in the current pattern and 0 if not in the pattern of document list. Corresponding binary output row is maintained which has same logic for tags of each pattern. Then the bag and output row are passed as training data to deep learning model where our X is the bag for patterns and y is output row i.e., tags for each pattern. Our deep learning model comprise of two dense layers with Relu activation and 1 output layer with SoftMax activation. We used Stochastic Gradient descent with Nesterov which accelerated gradient and gave good results. Finally, we used accuracy as our evaluation metric and the model is saved to be loaded when the GUI is executed.

3.4.2 Pattern Matching for NER

The other main module is the GUI module. When the Ecom-bot takes messages from a user, the regex initially allows finding the numbers in the message to find out which intent does the message belong to. If it has a number it checks from the previous intent stored whether it is the size, contact, house address or an order inquiry number. The response by chatbot is based on intent it identifies on current message. However. If it is not a number, it checks for entities by maintaining a sequence of conversation through its response. The entities like products, product categories, product colors, gender and size are extracted through regular expressions (regex). The entities are replaced with the corresponding keywords, such as bag to product or clutch to product category. This is to make sure that entities are properly mapped to one of the intents the chatbot is trained on. The transformed message is then passed to the model and the intents and probabilities are returned along with a potential response to the user. This continues until the user decides to end the conversation or the sequence of the conversation ends. Alongside there are logs maintained of each message, the raw message, its encoded version, predicted intents and response which are saved into csv and later used to search into product's csv and generate the product availability response or recommendation for user.

Once the sequence comes to the ending statement like 'type yes to complete the order' the Ecom-bot may look into the product's database to answer the user's query. To dig into the database, again a rule-based approach is used. The POS tagging is used to find the noun and verb chunks from the conversation logs to extract the relation between entities along with the entities themselves. The sentences are broken into chucks using the following rules shown in the Table 1. These rules allowed to cut the sentence i.e., where we had conjunction tag between noun and verbs etc. The chucks are further considered along with the corresponding predicted intents to extract entities through regex and allowed us to create a dictionary in which every product category became the key and it attributes became the values of the key. Finally, the dictionary is used to search the product(s) into the database along with the attributes allowing us to search accurately.

Table 1. Rules for sentence chunking using POS tags

Rules
“NN” or “NNS” and “CC” and “JJ” or “JJR”
“JJ” or “JJR” and “CC” and “NN” or “NNS”
“CD” and “CC” and ((“JJR” or (“JJ”
“CD” or “NN” and “CC” and “NNS” or “NN”
“NNS” or “NN” and “CC” and “NN or “NNS”
“CD” and “CC” and “VB
“VB” and “CC" and "CD"

In this way the following functions fetch order data, place order, notification through email on order placement, return or cancel order data and track order has been implemented in chatbot. The chat GUI in Fig 3 consists of a chat window that takes input from a user, processes it, passes it to the trained model and returns a response based on the user intent. The message/input undergoes multiple regex-based rules and POS tagging rules. This way, the Ecom-bot and user interact and the Ecom-bot asks relevant questions/queries and responds intelligently to the user.

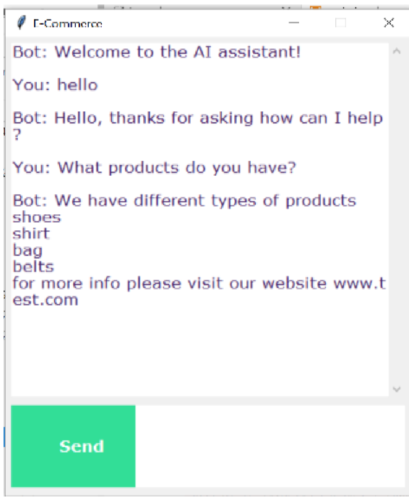

Fig. 3. The UI for the Input Messages in the Chatbot

3.4.3 Validity and Efficiency of the Proposed Approach

The Ecom-bot aims to develop a prototype to automate the customer service of an e-commerce site. The following are the major proof-of-concept milestones achieved through this work. It is needless to say that a successful deployment would have a lot of challenges of its own which are part of the future work.

- Possibility for the user to get from the chatbot:
  - answers to questions about the products and their services
  - completing a purchase without any human interaction
- Possibility for the user to make requests directly through the chatbot, such as:
  - Sending a request directly to the company’s customer service department so that it can be processed later
  - Recommending the alternatives when the product is not available
  - Placing an order for a searched product
  - Check the status of an order
  - Returning an order
- Designed new conversation scenarios based on user intents as NLU training data and chatbot responses in English in JSON file
- Using “custom actions” in the form of intents; thus, allowing the chatbot to validate forms and query CSV data in a form of a database
- Creating a dynamic response based on the user inputs.

4. Results

4.1 Results

With the combination of intents and the rules, Ecom-bot allowed to make an intelligent conversation by generating response according to the user's query. Table 2 shows the sample responses where the chatbot responded according to the nature of questions the user asked. For every user input the trained model predicts the intents through the information provided by the user in his input, by finding the highest probability and generates the response corresponding to the intent. Table 3 show the intents predicted by the model and their probabilities. The probabilities show that the chatbot could identify the intents with higher confidence. However, it also makes sure that the core information about the product is complete in a sequence of conversation therefore if the user misses any key attribute of a product, it would prompt the user to input that key attribute to make the search complete.

Table 2. Response generated by Ecom-bot

Sample 1: User: I want to buy bag Bot: Please specify the gender you are looking for and the product category for bag like clutch/tote/backpack/purse **Sample 2:** User: I want to buy bag for female Bot: what category are you looking for? Product category bag like clutch/tote/backpack/purse **Sample 3:** User: I want to buy backpack Bot: would you like to give more details? like what gender? female/male/boys/girls/kids **Sample 4:** User: I want to buy backpack for female Bot: would you like to give more details? like what size are you looking for? **Sample 5:** User: I want to buy pumps for female in color black Bot: would you like to give more details? like what size are you looking for? **Sample 6:** User: I want to buy pumps for female in size 9 Bot: would you like to give more details? like what color are you looking for?

Table 3. shows Model's Prediction on identifying intents along with probabilities

Intents	Probabilities
'intent': 'search'	'probability': '0.99999213'
'intent': 'search_product_by_gender_and_category'	'probability': '0.9999995'
'intent': 'search_by_product_category'	'probability': '0.9867784'
'intent': 'search_by_product_category_and_gender'	'probability': '0.9993795'
'intent': 'goodbye'	'probability': '0.99999774'

4.2 Conversations

The full conversation in proper form can be seen in Fig 4 & 5 where the user begins by asking for the product and the chatbot gradually asks user about the details of the product to acquire complete information about the product so that it could bring the searched item as per user's requirement. Fig 6,7, & 8 shows another use case where the user is asking for the bag and shoes and while answering to chatbot's question he missed out size of the product which tend to be important information for chatbot while searching for the product, so it can be seen in screenshots that how the chatbot carried the conversation to fill in the missing information.

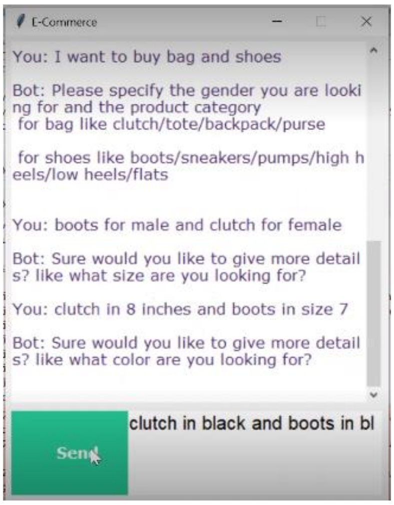

Fig. 4. Ecom-bot Conversation

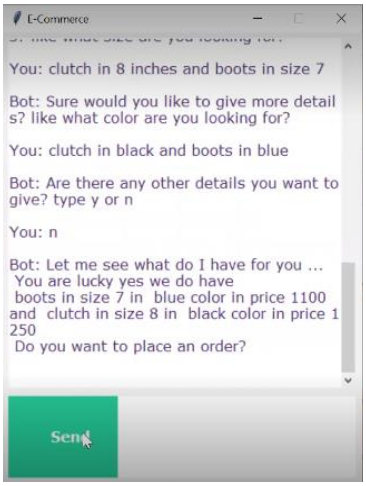

Fig. 5. Ecom-bot Conversation

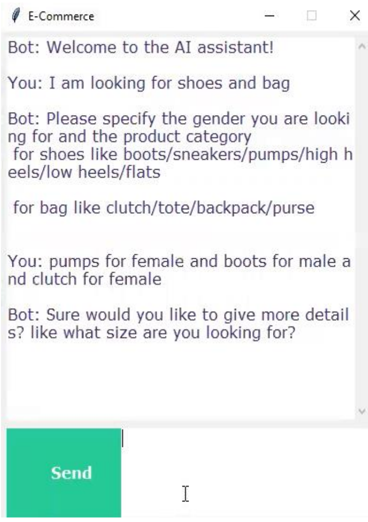

Fig. 6. Conversation with missing information

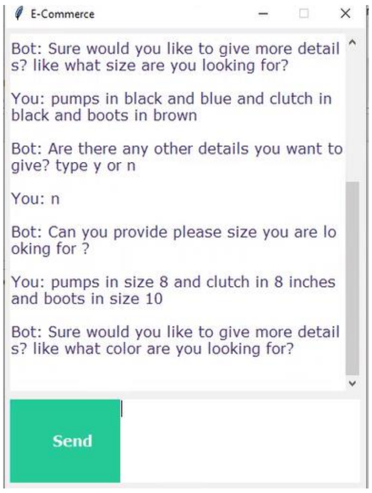

Fig. 7. Conversation with missing information

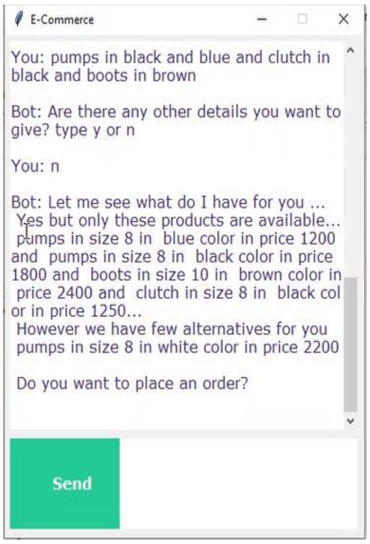

Fig. 8. Ecom-bot Conversation with missing information

5. Conclusion

Chatbots are ubiquitous today and improve work efficiency. They can reduce reliance on humans and answer questions intelligently in real-time. There is currently a great demand to use them for customer interaction in e-commerce, health, and other domains, as well as for social media marketing. In this project, the state-of-the-art in chatbots and their usage are briefly reviewed. Most of the existing research emphasizes improving the reaction/interaction of chatbots. In addition, more focus should be given to the significance of the user interface. There should be a standard framework for measuring the ability and quality of chatbots that does not exist in the existing literature. Additionally, improving the existing chatbots and their services demands a combination of different approaches. As shown in this work, a combination of deep learning and pattern matching can develop more efficient chatbots. Despite making significant progress, we faced several challenges, and fixing them is part of the future work. There were challenges related to identifying POS tags. The word masculine “male” is sometimes used as a noun or verb. The same problem occurs with “size”. Here the exception has been handled. But as the problem size grows, handling such issues becomes a challenge.

This product aims to contribute to the digital revolution and transformation of E-commerce industry and marketplaces. It has the potential to reduce human intervention on any online platform and conduct an intelligent conversation with the customer allowing him to search a product, place an order or inquire about his order. This could facilitate an easier process for people utilizing such platforms.

References

[1] Adamopoulou, Eleni, and Lefteris Moussiades. (2020). “Chatbots: History, technology, and applications.” Machine Learning with Applications 2: 100006.

[2] Bansal, H., & Khan, R. (2018). A review paper on human-computer interaction. International Journal of Advanced Research in Computer Science and Software Engineering,8(53), http://dx.doi.org/10.23956/ijarcsse.v8i4.630.

[3] Khanna, A., Pandey, B., Vashishta, K., Kalia, K., Bhale, P., & Das, T. (2015). A study of today’s A.I. through chatbots and rediscovery of machine intelligence. International Journal of U-and e-Service, Science and Technology,8, 277–284.http://dx.doi.org/10.14257/ijunesst.2015.8.7.28.

[4] Shawar,B.,&Atwell E. (2007). Chatbots: Are they really useful?.LDV Forum,22,29–49

[5] Brandtzaeg, P., & Følstad, A. (2017). Why people use chatbots. In I. Kompatsiaris, & etal.(Eds.),Internet science: Vol.10673.Cham:Springer, http://dx.doi.org/10.1007/978-3-319-70284-1_30

[6] R. Ranoliya, B., Raghuwanshi, N., & Singh, S. (2017). Chatbot for university relatedFAQs. In2017 international conference on advances in computing, communications, and informatics (pp.1525–1530). Udupi. https://doi.org/10.1109/ICACCI.2017.8126057.

[7] Costa, P. C. F. da. (2018). Conversing with personal digital assistants: On gender and artificial intelligence. Journal of Science and Technology of theArts,10(3),http://dx.doi.org/10.7559/citarj.v10i3.563, 2-59–79.

[8] Følstad, A., Bertinussen Nordheim, C., & Alexander Bjørkli, C. (2018). In Bodrunova S.(Ed.),Internet science:vol. 11193,What makes users trust a chatbot for customerservice? an exploratory interview study(pp. 194–208). Cham: Springer, http://dx.doi.org/10.1007/978-3-030-01437-7_16.

[9] Wallace, R. S. (2009). The anatomy of a.l.I.C.e. In R. Epstein, G. Roberts, & G. Beber(Eds.), the quest for the thinking computer(pp. 181–210). Dordrecht: Springer Netherlands, http://dx.doi.org/10.1007/978-1-4020-6710-5_13.

[10] Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. Computers in HumanBehavior,97,304–316. http://dx.doi.org/10.1016/j.chb.2019.01.020.

[11] Pamungkas,E.W.(2019). Emotionally-aware chatbots: A survey.ArXiv:1906.09774[Cs]. Retrieved from http://arxiv.org/abs/1906.09774.
[12] Trivedi, A., Gor, V., & Thakkar, Z. (2019). Chatbot generation and integration: A review.International Journal of Advanced Research, Ideas, and Innovations in Technology,5(2),1308–1311, XX.XXX/IJARIIT-V5I2-1840.
[13] Nimavat, K., & Champaneria, T. (2017). Chatbots: An overview of types, architecture, tools, and future possibilities. International Journal for Scientific Research and Development,5(7), 1019–1024, Retrieved from http://www.ijsrd.com/.
[14] Zhang, S., Dinan, E., Urbanek, J., Szlam, A., Kiela, D., & Weston, J. (2018). Personalizing dialogue agents: I have a dog, do you have pets too?. ArXiv:1801.07243 [Cs].Retrieved from http://arxiv.org/abs/1801.07243.
[15] Atwell, E., & Shawar, B. (2003). Using dialogue corpora to train a chatbot. https://doi.org/10.13140/2.1.1455.7122.
[16] Tammewar, A., Pamecha, M., Jain, C., Nagvenkar, A., & Modi, K. (2018).Production-ready chatbots: generate if not retrieve. AAAI Workshops.
[17] Biduski, D., Bellei, E. A., Rodriguez, J., Zaina, L., & Bertoletti De Marchi, A. (2020).Assessing long-term user experience on a mobile health application through an in-app embedded conversation-based questionnaire. Computers in Human Behavior,104, Article 106169. http://dx.doi.org/10.1016/j.chb.2019.106169.15
[18] Baudart, G., Dolby, J., Duesterwald, E., Hirzel, M., & Shinnar, A. (2018). Protecting chatbots from toxic content.(pp.99–110).https://doi.org/10.1145/3276954.3276958.
[19] Schuetzler, R. M., Grimes, G. M., & Giboney, J. S. (2019). The effect of conversational agent skill on user behavior during deception.Computers in Human Behavior,97,250–259. http://dx.doi.org/10.1016/j.chb.2019.03.033.
[20] Bernardini, Andréa & Sônego, Arildo & Pozzebon, Eliane. (2018). Chatbots: An Analysis of the State of Art of Literature. 1. 10.5753/wave.2018.1.
[21] Almansor, Ebtesam & Hussain, Farookh. (2020). Survey on Intelligent Chatbots: State-of-the-Art and Future Research Directions. 10.1007/978-3-030-22354-0_47.
[22] Zevik Farkash. (2018). Chatbots For Ecommerce — 4- ECommerce Challenges and Their Chatbot Solutions, https://medium.com/gobeyond-ai/chatbots-for-ecommerce-4-ecommerce-challenges-and-their-chatbot-solutions-6c8837f3c552
[23] Zevik Farkash. (2019). Ecommerce Chatbot — 4 Challenges Facing Ecommerce And How to Overcome Them Using Chatbots, https://medium.com/gobeyond-ai/chatbots-for-ecommerce-4-ecommerce-challenges-and-their-chatbot-solutions-6c8837f3c552

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How to cite this paper: Maria Zafar, " Developing Smart Conversation Agent ECOM-BOT for Ecommerce Applications using Deep Learning and Pattern Matching", International Journal of Information Engineering and Electronic Business(IJIEEB), Vol.15, No.2, pp. 1-10, 2023. DOI:10.5815/ijieeb.2023.02.01