Ecommerce Chatbot : E-Salesman

A Project Report

Submitted by

Prajakta Kamble 111708048
Nidhi Pusadkar 111708049
Riya Vidhale 111708051

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Under the guidance of

Prof. Archana Patil

College of Engineering, Pune

DEPARTMENT OF COMPUTER ENGINEERING

AND

INFORMATION TECHNOLOGY,

COLLEGE OF ENGINEERING, PUNE-5

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DEPARTMENT OF COMPUTER ENGINEERING

AND

INFORMATION TECHNOLOGY,

COLLEGE OF ENGINEERING, PUNE

CERTIFICATE

Certified that this project, titled "Ecommerce Chatbot : E-Salesman" has been successfully completed by

Prajakta Kamble	**111708048**
Nidhi Pusadkar	**111708049**
Riya Vidhale	**111708051**

and is approved for the partial fulfillment of the requirements for the degree of "B.Tech. Information Technology".

SIGNATURE

Prof. Archana Patil
Project Guide
Department of Computer Engineering
and Information Technology,
College of Engineering Pune,
Shivajinagar, Pune - 5.

SIGNATURE

Dr. Vahida Attar
Head
Department of Computer Engineering
and Information Technology,
College of Engineering Pune,
Shivajinagar, Pune - 5.

Abstract

Online shopping through e-commerce websites is the new trend rather than traditional ways of purchasing anything. Chatbots are the AI based programs included in such e-commerce platforms to help the users to explore more about website and various products to reduce the human to human interaction. Human to human interaction turns out to be slow, error prone and lacks the availability factor. Our goal is to design the e-commerce chatbot to make conversing smoother. Proposed design aimed to take order with minimal user input and suggested for target markets where customers have little knowledge of IT, where they don't know how to navigate through sites to find the right product. The motivation of the work comes from the literature review, where we found out the shortcomings in traditional methods to interact with customers. We tried to identify the possible shortcomings of already existing designs through various research papers and then chose to design chatbot overcoming some of these shortcomings using the proposed solution.

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Chapter 1

Introduction

E-commerce businesses used traditional methods like call centers and websites for interacting and communicating with the customers. But these methods were replaced with chat and voice based assistant software as technology innovations leveraged. Most of these past chat based assistant software was implemented for keyword search engine which leads to basic machine learning system. So the first and second generations voice chat assistants proved to be failed, then third generation chat assistant software were introduced which are called as Chatbots.

They are based on latest technology referred as AI(Artificial Intelligence). The computer program which make use of artificial intelligence to initiate a coherent conversation with humans is referred as chatbot. In chatbots, one can ask queries, give answers which is recognized by chatbots using Natural Language Processing. Chatbot services like chatterbot used for automation, which helps to automate business processes for different industries and sectors such as e-commerce industry. We can refer it as communication between human computer interaction and human-human interaction. Chatbot services are also being implemented as SaaS(Software as a service) solution.

Nowadays most people own a smartphone with instant messaging or social networking applications on them and they may use these applications to interact with merchants and seller. With the help of chatbot seller can easily communicate with customers. A chatbot is a tool for this kind of interaction which can understand the context and deliver an appropriate response to the customer.This king of interaction is also known as Chat-commerce. According to Chris Messina chat-commerce definition is "using talk, informing, or other characteristic language interfaces to connect with individuals, brands, or administrations and bots that hence have had no genuine spot in the bidirectional, non-concurrent messaging context."

Chapter 2

Literature Review

2.1 Introduction

Nowadays, ecommerce websites are using Chatbots to provide services such as customer support for product enquiries and seamless transaction checkouts. Using this new technology, customers can get any information by simply interacting with the Chatbot. Chatbots can be used to provide responses to the customer queries 24x7.

Connecting buyers and sellers through human intervention cannot provide proper communication and can make customers remain in vagueness. In this context, Chatbot services could transform the ecommerce business sector. Chatbots allow ecommerce sites to provide more to their customers without the need for human intervention. a simple conversational chatbot should be added to the ecommerce website which can help customers pick the right product according to their needs.

The main difference between customer support staff and Ecommerce Chatbot is that customer support staff can provide only few services whereas Chatbot can communicate with user ,help them to find the product they are looking for making the customer satisfied.

2.2 Workflow

According to [1], The following steps depict the architecture of a fundamental ecommerce chatbot service. The steps include:

Step 1: Customer sends a message or request to chatbot and connection will be established with the presentation layer. This message will be sent to the messaging backend. A customer will have a conversation with the chatbot stating the needs and criterias for the buy.

Step 2: The user query/ request will be processed by the messaging backend using natural language processing methods and converted to codified commands and sent to the decision engine.

Step 3: The decision engine will have a predetermined criteria which must be met for the command to exit the conversational loop.

Step 4: The codified commands are sent to either the natural language generator or the data layer depending upon the type of request.

Step 5: Structured data is converted into text by natural language generator. If more information is needed, data from the data layer is used.

Step 6: Feedback generated by the natural language generator will be sent back to messaging backend. This feedback will be sent to the customer as question response. This conversation will reiterate until customer is satisfied.

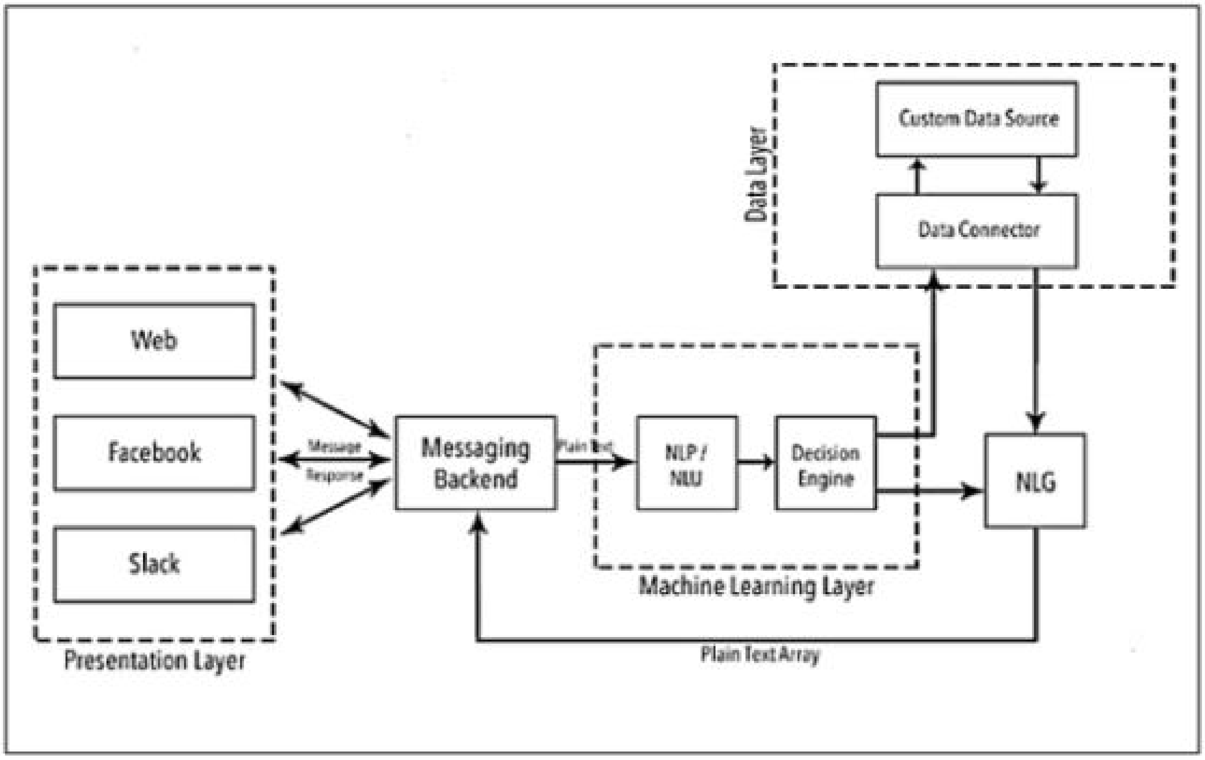

Figure 2.1: Chatbot Service Architecture

2.3 Use cases

In e-commerce websites, Chatbot services provide the following functions:

- Shopping helper: E-commerce websites have a wide range of products which are dispersed across various web pages and categorised according to their features. To locate relevant product, the user have to navigate through all these webpages and categories. This can be very cumbersome, and even frustrating for those who don't get lost in the oceans of products. A Chatbot can be of help by providing a natural way of interacting with the website and its range of products.

- Customer care: FAQs and repeating can be answered at anytime on any day without much of a human interaction. Some of the FAQs about the product can be answered by our chatbot, and if the user is wants to talk to a human, that provision can also be provided.

- Payments: The purchase transaction can be completed using the Chatbot service. But when the payment gateway integration is concerned, there are many security aspects to take care of while implementing.
- Shipment tracking: A Chatbot service can be used to automate the reponses to the enquiries regarding an item's shipment.

New Chatbot applications can be made incorporating new technologies like Blockchain, AI, and NLP in the functioning operations of the chatbot. Chatbot technology is growing at a fast pace and more improvements will lead to providing better customer experiences with low costs.

2.4 Benefits

2.4.1 For Customers

- Availability
- Instant and consistent replies
- Improves overall customers experience
- Self Learning chatbots can perform better giving user oriented replies.

2.4.2 For E-commerce website

- Cost optimized solution
- Increased customer satisfaction
- Increased in customer interaction and sales
- Optimized information management
- Error prone manual tasks are automated

- Helps in acquiring new customers
- Can be used as a business tool which provides detailed data about concerns which customers are facing and the customer feedback which can used for improving business products and services.

2.5 Concept Description

[2] mentions that a potential customer looks for specific product while visiting an E-commerce website. In this context, search tools use matching keyword method which shows more than one results for respective user's query. Some of these results might be not relevant which lead to low accuracy. It can lead to low usability as user might not find the correct product. Also it is possible that system itself may not show correct product. When user is just browsing the website and is unaware about product he/she wants to purchase, conventional system might not be supportive for the user. Hence e-commerce chatbot intends to resolve mentioned problems by helping user to interact in more natural way with the websites. It interacts with users and suggests correct products to them.

According to mentioned in [3], There are three types of chatbot sub-engines-

1) For Product information - a factual QA engine

2) For answering FAQs - FAQ engine

3) For Customer Reviews - an opinion mining and text QA engine.

2.6 Related Works

1. **A Chatbot for an E-Commerce Website [2]**

   Functionalities:

- For this chatbot Riverscript language is used, for integration PHP is used and for storing data MYSQL database is used.
- Response time of this chatbot is very small. According to user's queries and requirements, this chatbot can give responses and suggestions. Also it can ask other questions to collect the required information from user.

2. Implementation and design of an e-commerce chatbot [4]

Functionalities:

This chatbot can answer the questions like in a conversational form:

- Customer : What is the latest product in category q? Chabot sends the product details of five recent products in category q.
- Customer : What is the product with price less x in category q? The Chabot sends the product details of the five cheapest products with price than x in category q..
- Customer : What is the best seller product in category q? The Chabot sends product details of five products that have the highest total sales in category q.
- Customer : What is the best product in category q? The chatbot sends product details of five products that have the highest rating in category q.

3. Design of E-Commerce for Computer Hardware and Books with AI Enable Chatbot [5]

Functionalities:

- In this chatbot, already programmed reactions and responses are stored although user can give dynamic input which will provide relative and relevant responses.

- New products of different categories can be added and deleted easily without modifying the responses stored in chatbot, because database of product is not dependent on the stored responses and answers.

4.Super-Agent: An E-commerce Website chatbot for Customer Service [3]

Functionalities:

- This chatbot uses large and crowded data related to customers which is available publicly.
- It also uses machine learning techniques and natural language processing along with fact based questions answers, Frequently Asked Questions, chit chat conversing model, questions answers based on opinion oriented text.

2.7 Techniques

2.7.1 Pattern matching(FAQchat approach)

- In the approach used in [2], the javascript interpreter runs on client browser and the responses which is known as the brain of the bot is stored in '.rive' simple text file. It uses a large set of pattern matching templates instead of natural language processing and logical assosciations.
  Conventions in rivescript:
  '-' indicates the chatbot response
  '+' indicates a trigger i.e a user input or query.
  Using these conventions, user query is matched with the stored triggers by the interpreter and it chooses the most fit response to user query.
- In Rivescript, we can also set user variables using parts from user queries,

and bot variables can be pre-programmed , conversational redirects, wild cards,Javascript object macros

- As the responses are not hardcoded, chatbot will provide the latest details depending on the updated database.

2.7.2 Fact based Questions answers for Product Information

- In [3], Fact based QA Engine is used to answer features related questions for a product.
- The product information is stored in the format of knowledge triplets (product name, attribute name, attribute value).
- Using a matching framework, it matches the input question with the knowledge triplets and the top-ranked result is selected.

2.7.3 Frequently Asked Questions Search for customer QA pairs

- In [3], A set of QA pairs P = {qi, ai} is given. For a customer's query q, find the most similar qi in P and return the corresponding ai as the response.
- Train a regression forest model and used the features like monolingual word aligner, DSSM model, n-gram overlap, subsequence matching, PairingWords, word mover's distance.
- In case of multiple answers for the same question, ambiguous user query may yield unsatisfactory results.

2.7.4 Opinion-Oriented Text QA for Reviews

- In opinion mining, [3] uses a hybrid approach to extract the features from review sentences.
- Using the sentiment classifier it determines the polarity (i.e. positive, negative, and neutral) of the sentence with respect to the specific feature extracted. The feature and polarity are indexed together with keywords using the Lucene toolkit2.
- For text QA engine, given a user querythe response is formed in the following three phases :

  1. Search user query by Lucene to get probable candidate sentences : Candidate retrieval.

  2. Rank all the candidate sentences using a regression based framework for ranking : Candidate ranking.

  3. Decide which candidate has the highest rank, and based on the confidence use it as a response : Candidate triggering.
- Determining polarity of an ambiguous review is a challenging task.

2.7.5 Chit-chat Conversation Modeling

- This is conversational model based on long-short term memory recurrent neural network seq2seq model which is trained on conversation data of twitter.
- it is basically used for replying to greet queries like "hello", "thanks". It has already define response set from which it extract responses using small reply approach, it will avoid non-relevant queries such as "you are nice".

- Response set consists of most frequent five million unique short replies are selected. The engine's output is very topic coherent.

  Example:

  User: hello

  Chatbot: hi! how are you?

  User: thank you!

  Chatbot: you're welcome!

  User: you are nice

  Chatbot: you too

2.7.6 Seq2Seq Approach

- Seq2Seq Approach model is also known as encoder-decoder model.

- For generating text from the training corpus, it uses Long Short Term Memory (LSTM).

- It calculates the probability of a word to occur given the user input. Using this, it predicts the likelihood of next sequence of words given the previous word.

- Then the encoder sends the output i.e. a final state vector to the each layer of decoder. "END" token is added at the end to stop the decoder. Example :'Hi,', 'how', 'are', and 'you' are called input tokens while 'I', 'am', and 'fine' are called target tokens.

2.7.7 Google Neural Machine Translation (GNMT)

- Google Neural Machine Translation (GNMT) uses ANN to help Google Translate improve its accuracy.

- GNMT is used for dialogue generation using Seq2Seq model.

- GNMT model include many models such as Sequence to Sequence (famous for dialogue generation) modeling with an encoder-decoder architecture built using uni/bi-directional LSTM cells, Neural Attention Mechanism, Beam Search, and vocabulary generation using Google's sub-word module.

Chatbot	Input/Output	Technique	Drawback
Eliza	input : Pattern template, output : Reordering	Template based	No logical reasoning capabilities, inappropriate responses
Alice	input : Input rules, keywords sequence matching output : Output rules	Recursive	No derivation structure of sentences
Elizabeth	input : Input rules, output : transformation rules	Iterative	Does not split input and recombine outputs
Mitsuku	input : AIML, output : wild card + core	supervised ML, context and numeric frequency	Does not provide dialogue components
Cleverbot	input : keywords matching, output : previous chats	Rule-based	Inflexible conversation flows
Watson	input : feature values, output : score	Rule-based	Does not process structure data. No relational databases
Dialogflow	input : intents, entities, output : random from the list provided	intents : Supervised ML, entities : Entity recognition and extraction	No interactive UI and does not support handheld devices

Table 2.1: Comparison of different chatbots

Chapter 3

Research Gaps and Problem Statement

3.1 Research Gap

While doing the literature review, we came across some shortcomings of the design approach of chatbot that prevented efficient and effective conversation.

3.1.1 Predefined/ Closed Domain

In this approach hardcoded request, response pairs are embedded in the system. A query is matched to a request, resulting in the corresponding response.

Shortcomings

- They perform well as long as the queries are matched with the existing queries fed to them. The moment they get an unknown query, they handover the conversation to a human (or some failure handling system). These type of chatbots are not standalone, they require human intervention at some point of time to add the unknown queries and its proper response in the system.
- The responses can be pretty repetitive, and only a fixed number of

queries those defined in the system can be handled.

- It is near to impossible to embed every possible request, response pair into the system.

3.1.2 Fixed rule based chatbots

In this approach there are fixed set of association rules embedded into the chatbot. A query is matched with the condition of a rule using a template based matching algorithm. After a query is matched, the corresponding action set is implemented.

Shortcomings

- They perform well as long as the queries follow the conditions of one of the embedded rules fed to them. The moment they get an a query not matching to any rule conditions, they handover the conversation to a human (or some failure handling system). These type of chatbots are not standalone, they require human intervention at some point of time to add the unknown queries and its proper response in the system.

- They lack in providing personalized communication, or in using semantic meaning. Template matching of every style of communication can't be embedded in the system for example, "I want to buy a laptop" and "I am interested in purchasing a laptop" should be matched to same template as they are semantically similar.

- It is very challenging for the developer to embed every possible scenario as rules of conversation into the system.

3.1.3 Spelling Mistakes

Some chatbots don't take into account the possibility of spelling mistakes in the user query. This can result in inappropriate responses.

Shortcomings

- One of the two cases might happen :
  - The chatbot doesn't match user query to any intent and leads to failure default message.
  - The chatbot matches user query to some random intent leading to incorrect response.
- Both the scenarios are not ideal for a seamless conversation.

3.1.4 Language Structure/ Syntax

Some chatbots does not take into account different sentence making structure in a language. For instance, structure of text, use of punctuations, nouns and spaces differ in different sentence styles in a language. Existing chatbots are not able to detect the difference. This especially happens when the chatbots use bag of words model for keyword matching.

Shortcomings

- Language structure is very much important in determining the intent of the user query.
- Not taking it into account will definitely hinder accuracy of the intent classification

3.1.5 Semantics

Some chatbots which employ bag of words model, not using the language models are not able to do the semantics analysis which is processing the user query based on the meaning and context.

Shortcomings

- Semantics is equally important as the syntax of a user query in determining the intent of the user query.
- Not taking it into account will definitely hinder accuracy of the intent classification

3.1.6 Grammatical Errors

Processing syntactically or semantically incorrect sentences which in turn will lead to grammatically incorrect sentences, will result in chatbot failure to understand the literal meaning of what the user is saying. Some chatbots typically the ones employing fixed template based/ pattern based matching, don't have a provision to handle the grammatical mistakes that can be made by the user.

Shortcomings

- They don't perform well when user query is not grammatically correct. Either of two cases could happen :
  - The query are misinterpreted to some random query giving an incorrect response.
  - It leads to a failure response or human intervention.

3.1.7 Ambiguity

Some chatbots are not able to handle ambiguity. Ambiguity occurs when a query given by the user can be interpreted in more than one way. The chatbots which don't have functionality of handling ambiguity are not able to perform well in response to such queries.

Shortcomings

- When a chatbot gets an ambiguous input, it'll not be able to create a definite response corresponding to the user query, because it isn't prepared to do so.
- There can be one of the following responses from the chatbot in such case :
  - A chatbot selects one of the possible interpretations on its own.
  - A chatbot gives response corresponding to every possible interpretation.
  - A chatbot fails disrupting the conversation.
- None of the above cases are favourable and leads to undesirable state where the chatbot fails and conversation breaks down.

3.1.8 Sentiment Analysis

Some chatbots are unable to detect the sentiment (implicit feedback) of the user in a conversation. This can be done by by analysing the query and how the user talking, or by asking explicitly. The chatbot should keep track of feedback from the user using speech pattern from the user queries and determine whether the human is satisfied or not, to improve the responses. This can be used as a feedback loop.

Shortcomings

- If a chatbot is not able to determine the sentiment of the user while conversing, this may lead to increasing dissatisfaction of the user.
- It may also lead to query drift, if the user expresses dissatisfaction, but the chatbot don't know how to change the flow of conversation and the user feedback queries are continuously kept on matching to inappropriate responses.

3.1.9 Recommendation System

Most of the chatbots do not ask followup questions to the user. Nor do they explain or give advice to the user based on the current context. They just collect user query, extract information and provide responses from their output database. The chatbot should able to ask questions to the user based on previous answers.

Shortcomings

- If a chatbot is just providing the information, it may lack a major part of conversation i.e. asking questions.
- It may also lead to query drift, if the chatbot didn't ask for confirmation if the conversation is going in the right flow.

3.1.10 Accuracy

Chatbots are programmed to have a seamless conversation with the user to accomplish a task. This will make sure that the user gets what they intended to gain from the conversation. However, existing chatbots generate unpredictable responses. They sometimes suddenly change the subject and respond without context. Thus, the accuracy is not achieved at a satisfactory level.

Shortcomings

- Low accurate responses, lead to frustration of the user.
- It may also lead to failure of the whole purpose of chatbots i.e. seamless conversations.

3.1.11 Self-Learning

The chatbots are not able to learn from new user queries and do not use supervised machine learning algorithms for training.

Shortcomings

- Iterative need to update the request, response pairs or association rules.
- Not able to map an unknown/ new user query to appropriate intents.
- Hard matching is not possible for every user query.
- Not able to learn from the unknown queries that they encounter.

3.1.12 Third Party Integration

Because of unavailability of plugins/ scripts required, embedding of existing chatbots in a webpage is difficult.

Shortcomings

- Enterprises can't use them to improve their sales.

- These chatbots are not able to reach more people, which restricts the amount of training data and are not able to learn and improve from user queries of various kind.

3.2 Problem Statement

To implement a smart and a responsive chatbot which will communicate with the user(like a salesman) in natural language, understand the product the user has been looking for and provide the recommendations(urls) of the products as per the customer's need. The chatbot can be used for product exploration as well, wherein the user can get information about any product.

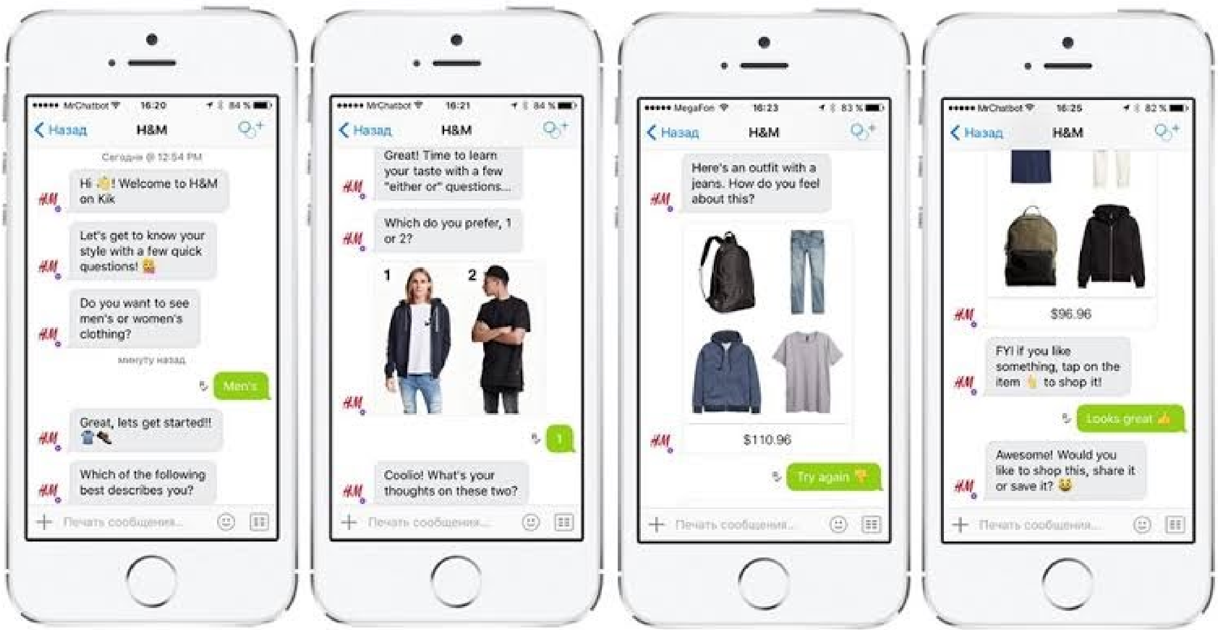

Figure 3.1: A Prototype

3.3 Objectives

1. To study existing e-commerce chatbots system design and techniques used.

2. To design an e-commerce chatbot which helps users choose the right product.
3. To measure the accuracy of the responses during the session for the designed chatbot.

Chapter 4

Proposed Methodology/ Solution

Some of the shortcomings we have tried to address and proposed a solution.

4.1 Dataset

This chatbot will be integrated with e-commerce websites, so the dataset used is consisting of fields -

- Product Name
- Product Price
- Product URL
- Product Ratings
- Product features in form of (attribute name, attribute value) for instance (RAM, 4GB)

4.2 Preprocessing

4.2.1 Sentence Level

Minimize the probability of input of sentences from user. This is done by adding buttons, suggestion chips, and providing expected answers using accordions.

4.2.2 Word level

Spelling mistakes - A spell checker module to determine whether each word has a meaning independently. If not find the most closest possible word.

4.3 Entity recognition

Train the entity recognition module for each category to extract the corresponding feature values (eg: For Mobile category, train the Entity Recognition Module to extract Brand, Colour, Memory size).

4.4 Follow ups

We identify which features that are required to filter products. Until we get all the required feature values, we keep asking the user for feature values of remaining features. (eg: For Mobile category, we check if we have got Brand, Colour, Memory size from the user, else we ask user to provide the values for the remaining features.) The most recent feature value will be considered and saved.

4.5 Sentiment Analysis/ Feedback

We ask the user to confirm if they want to continue with the feature values they have entered till now. If the user wants to continue, we ask them the price range, else we again start asking them for the new feature values required by them.

4.6 Product Information Handling Module

- Trigger the appropriate product information handling module using button triggers (eg: Clicking on Mobiles, will trigger the mobile handling module).
- Use Entity recognition, Follow ups, Sentiment Analysis/Affirmation modules to get all the required features to find the product from the user.
- Pass the features to the Product Recommender module.

4.7 Product Recommender Module

- Constructive method - Start with an empty list and add the products which have the features entered by the user to the list. If there is no such product available, add the top 5 products from the same category for the brand the user entered to the list.
- Elimination based approach - From the constructed list of potential products, eliminate based on the price range user selected and output the final list of products to the user.

4.8 Product Recommendation Feedback

This feedback is used to calculate the accuracy score of the chatbot.We ask if the user is satisfied with the products we recommended based on the features he entered.

- If the user is satisfied and says yes, redirect him to the Session Feedback module.

- If the user is not satisfied, Ask if he wants to see the Top Rated Products for the brand he wanted.
  - If he says yes, output the top 5 products for the corresponding brand. Again call the Product Recommendation Feedback module.
  - If he says no, call the Session Feedback module.

4.9 Session Feedback

At the end of the session, we ask the user to rate his experience of using the chatbot. This feedback is used to calculate usability score of the chatbot.

Chapter 5

Experimental Setup

5.1 System Requirements Specification

5.1.1 Functional Requirements

- Users will be able to converse with the Chatbot through text commands and it will understand what the user is saying through natural language understanding provided through the integration of Dialogflow API.
- The chatbot should be able to maintain the conversational state when the context may be unclear through previous messages and conversations.
- The chatbot should provide the link to buy the product chosen by the user.
- The chatbot should be able provide text responses.
- The chatbot should be able to consider feedback and change the response accordingly.

5.1.2 Non Functional Requirements

- The chatbot must be efficient with very little lag in response time for instance no longer than 5 seconds to reply to a user message.

- The chatbot must be reliable with next to no faults or bugs.
- The use of natural language used to interact with the chatbot promotes human computer interaction.
- Provide accurate responses to input.
- Appropriate handling of unexpected input and correctly inform the user if it cannot provide.

5.1.3 Software Requirements

- Dialogflow
- Ngrok
- Flask

5.1.4 Hardware Requirements

- PC running Linux-Ubuntu to host chatbot locally
- Processor – intel core i3

5.2 Data Collection

We collected a dataset for Electronics category our E-commerce chatbot. We have used web scrapping method to collect the data from Amazon website. We have used Selenium Chrome webdriver to scrape records. For extracting information needed we have used BeautifulSoup library in Python. After extracting respective category, the data is collected inside CSV file which will be ultimately used to fetch product link according to the features entered by the user.

5.3 Chatbot Working

1. Provide user with options in which category he wants to browse and trigger the corresponding category module.

2. For the category chosen by the user, ask him for the feature values required to find the products in that category.

3. After getting the required feature values, confirm with the user if he wants to continue. If No, go back to asking feature values.

4. Ask user for the price range.

5. Find the products based on the features and price entered by the user.

6. Ask if the user is satisfied with the recommendations. If no, ask if he wants to see the bestsellers/ top rated products for the brand he entered. If yes, output top 5 products from the category of the brand user entered and ask if the user is satisfied with the recommendations.

7. Ask the session end feedback.

5.4 Integration

We have used Dialogflow Messenger to take advantage of buttons, accordions, and suggestion chips. Then we have integrated this UI with the Dialogflow intent classifiers which triggers the action required to process the query. Then we send this processed user query to the Flask server using webhook. And Flask server returns the responses using webhook.

5.5 Rating

Although rating a chatbot performance can be subjective, but we have tried to use the fundamental approach. We rate the chatbot in two ways :

1. Accuracy Score - Ideal accuracy score should be 2.

   - Whenever we couldn't extract the features accurately, user will have to re-enter the features, in this case accuracy score is deducted by 1. Else if the user says continue with the features (assuming the features are extracted correctly) accuracy score is incremented by 2.
   - Whenever user is not satisfied with the results, current accuracy score is deducted by 1. And if the user is satisfied with the links provided accuracy score is incremented by 2.

   Finally the accuracy score is normalised by the total number of rating rounds.

2. Usability Score - This is determined by the end of session feedback given by the user. If the user rates the experience as Not good, Nice and Great then the usability scores given are 0, 3, and 5 respectively.

1 1

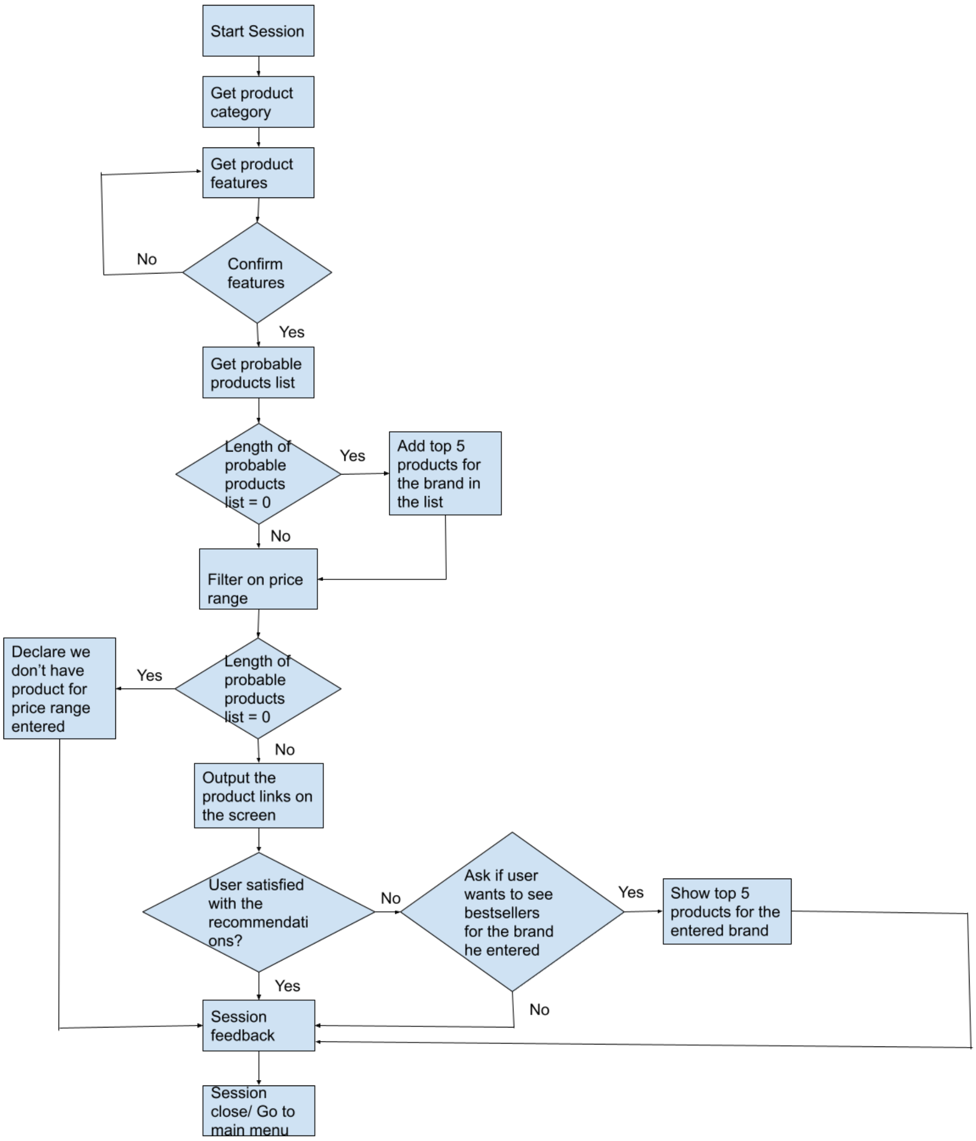

Figure 5.1: Flowchart

Chapter 6

Results and Discussion

6.1 Working of e-Salesman

Here is how the chatbot will look when integrated with e-commerce website.

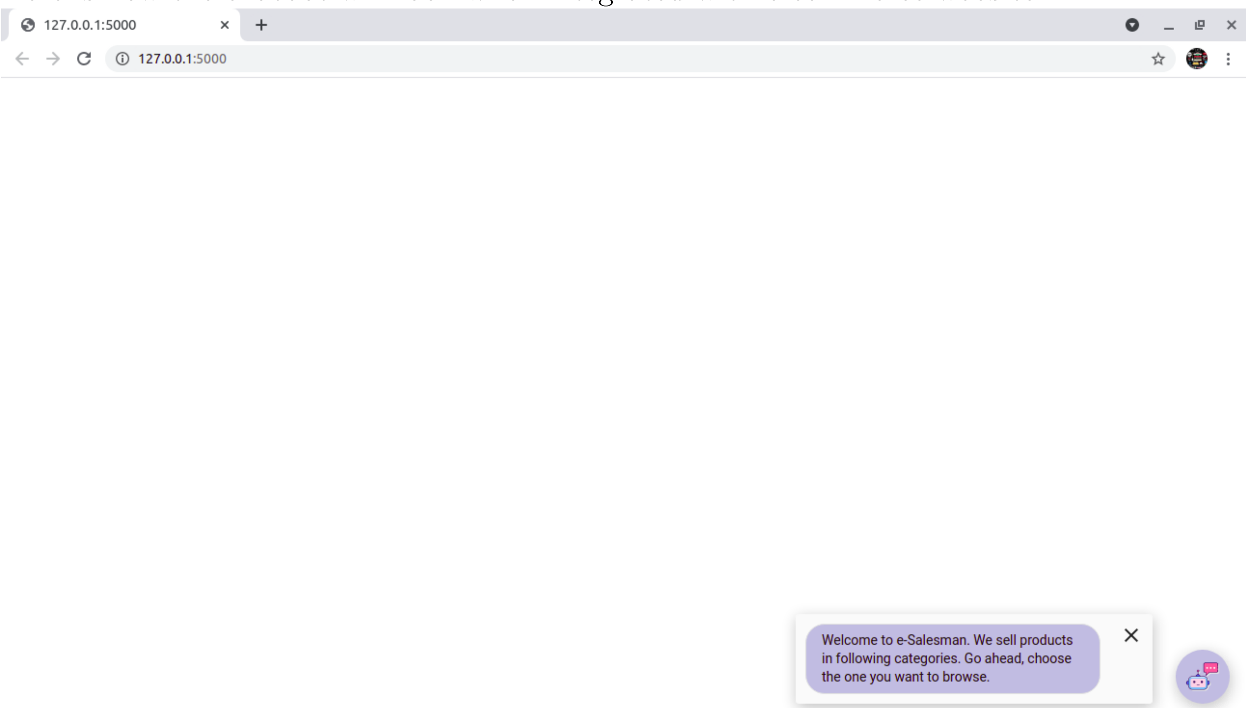

Figure 6.1: Welcome Screen

We provide links to the user based on the features he entered and ask for the feedback (Product Recommendation Feedback).

To minimize the input of sentences, we have added these suggestion chips to select the categories and subcategories.

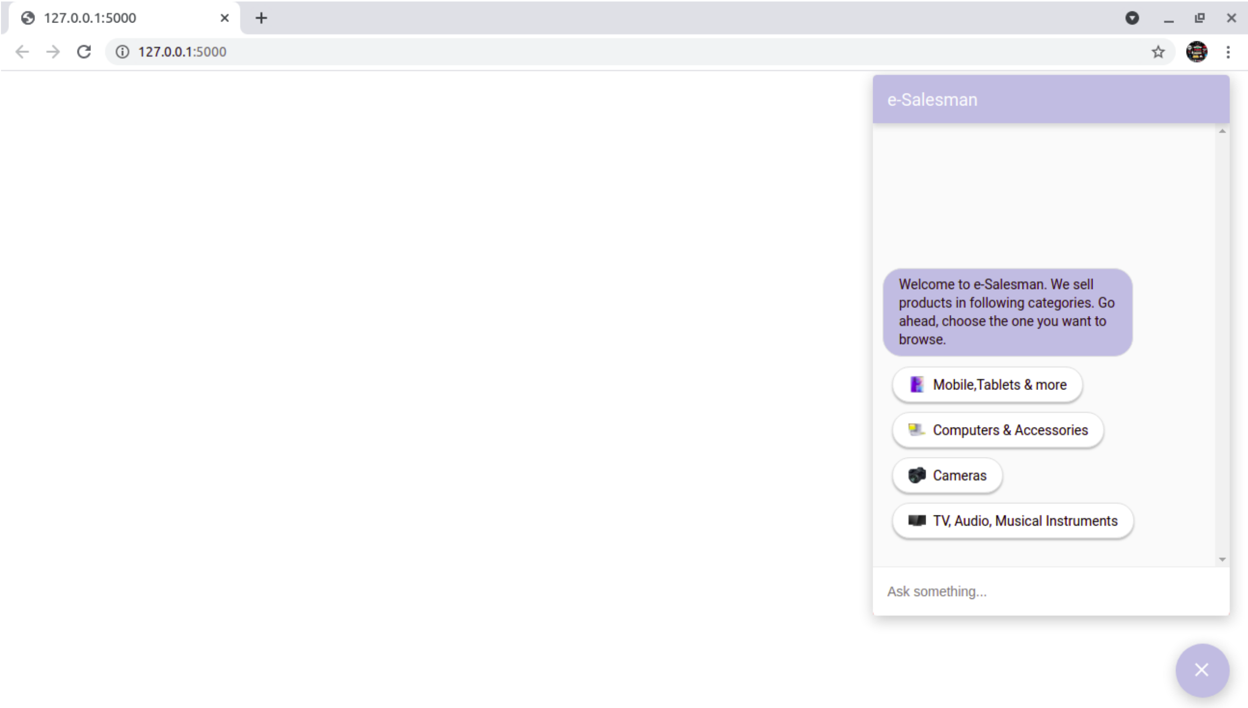

Figure 6.2: Product Category List

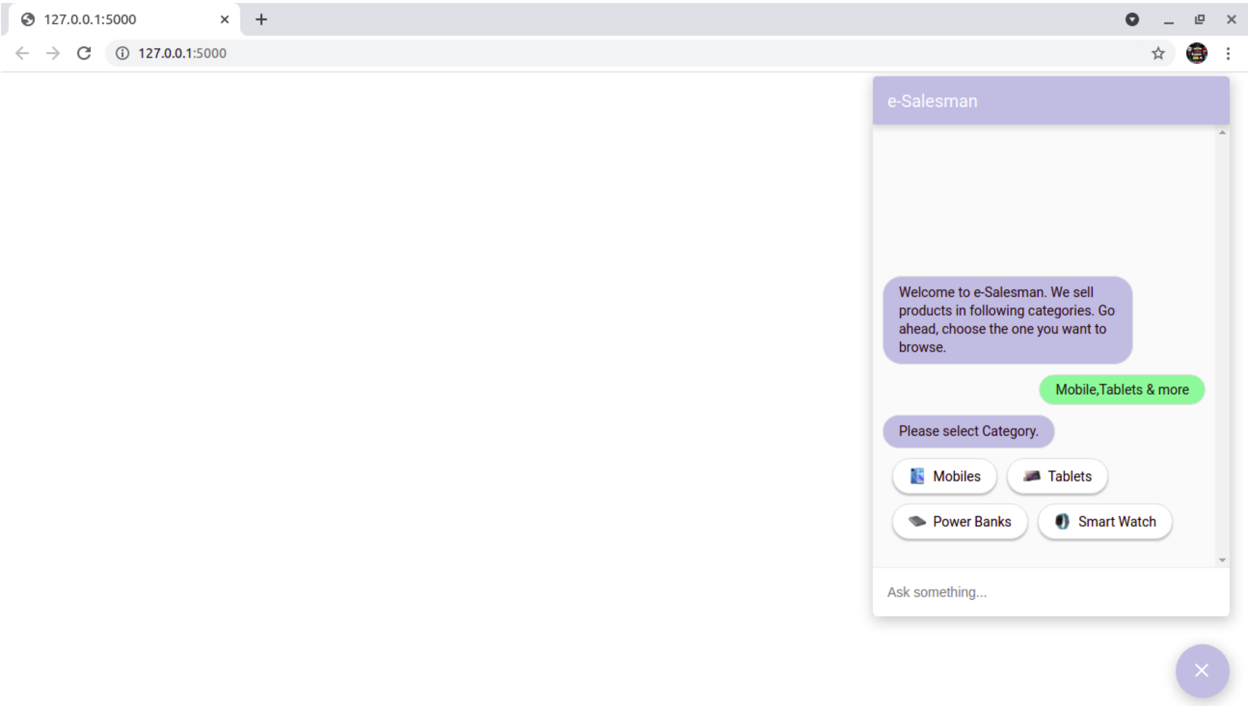

Figure 6.3: Product Subcategory List

After selecting the category, it will ask user to enter all the required features to recommend the product (Here, Followup with required feature : colour). The accordions will help the user to enter the input that is expected. It will handle spelling corrections, and extracts the entities as well.

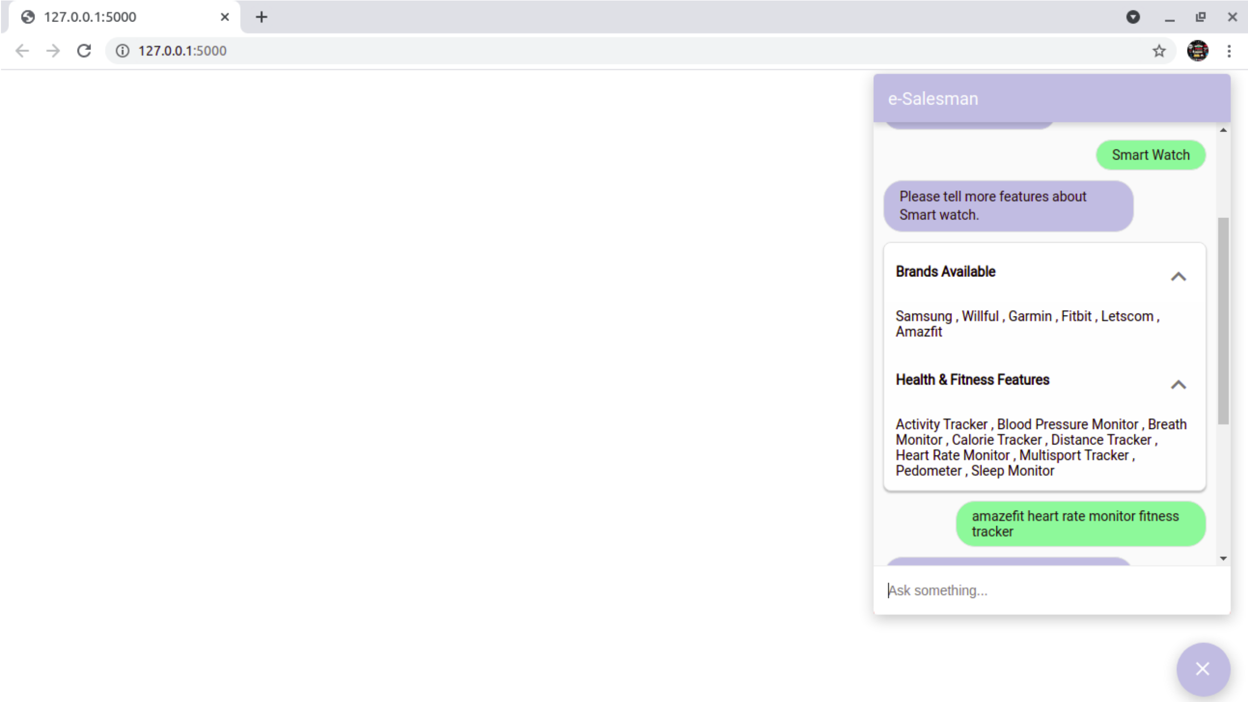

Figure 6.4: Input Product Features

Here is the Affirmation asked to the user, whether he wants to continue with the features he entered.

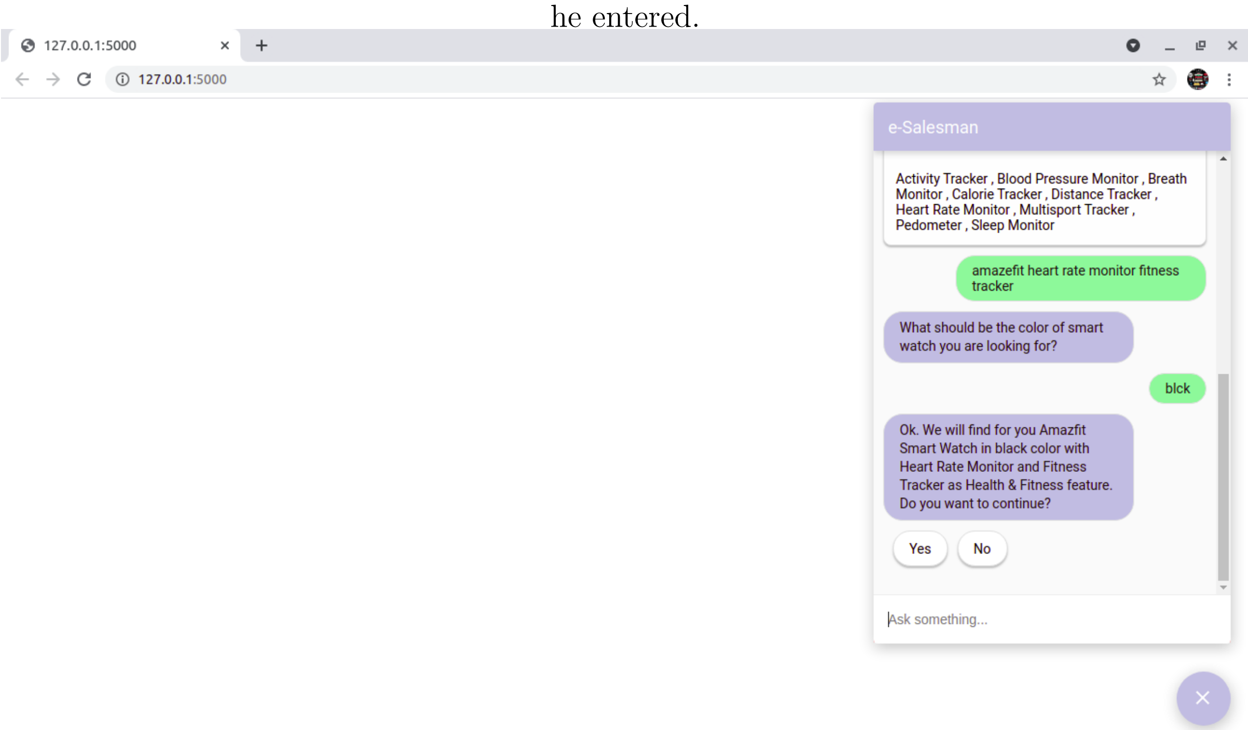

Figure 6.5: Affirmation of features entered

After user says "Yes", then we ask the user which price range he wants the product in?

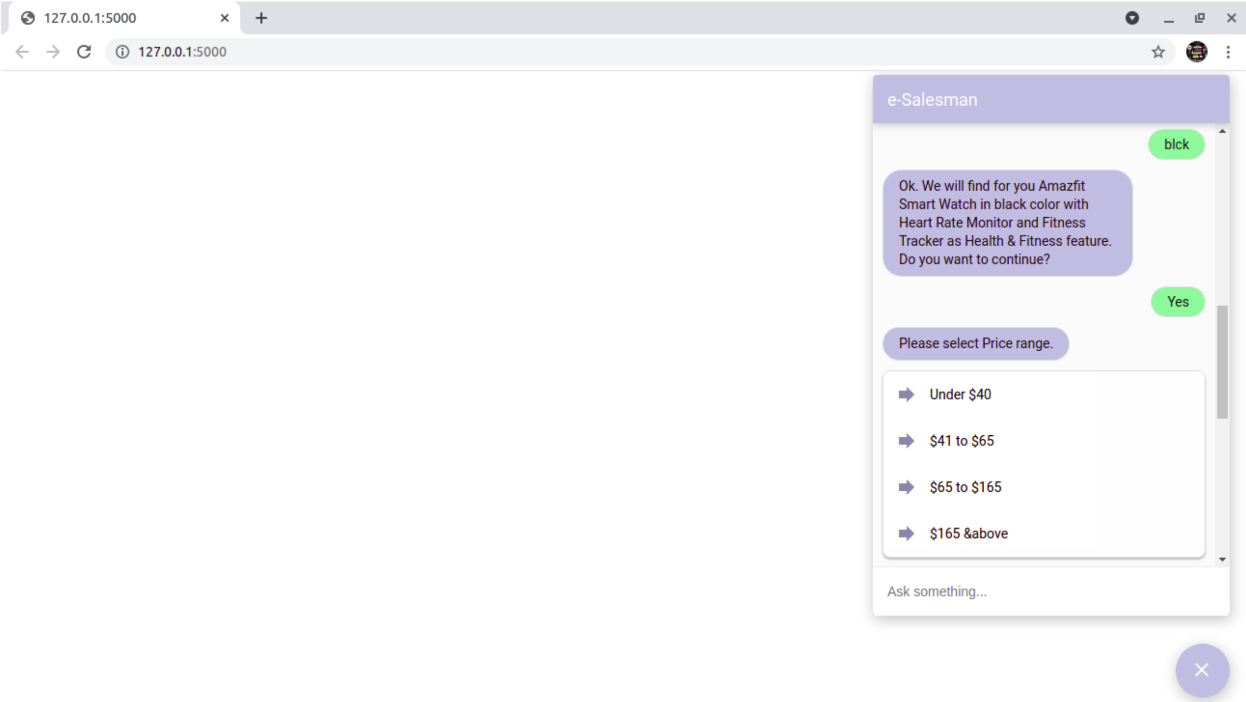

Figure 6.6: Product Price Range

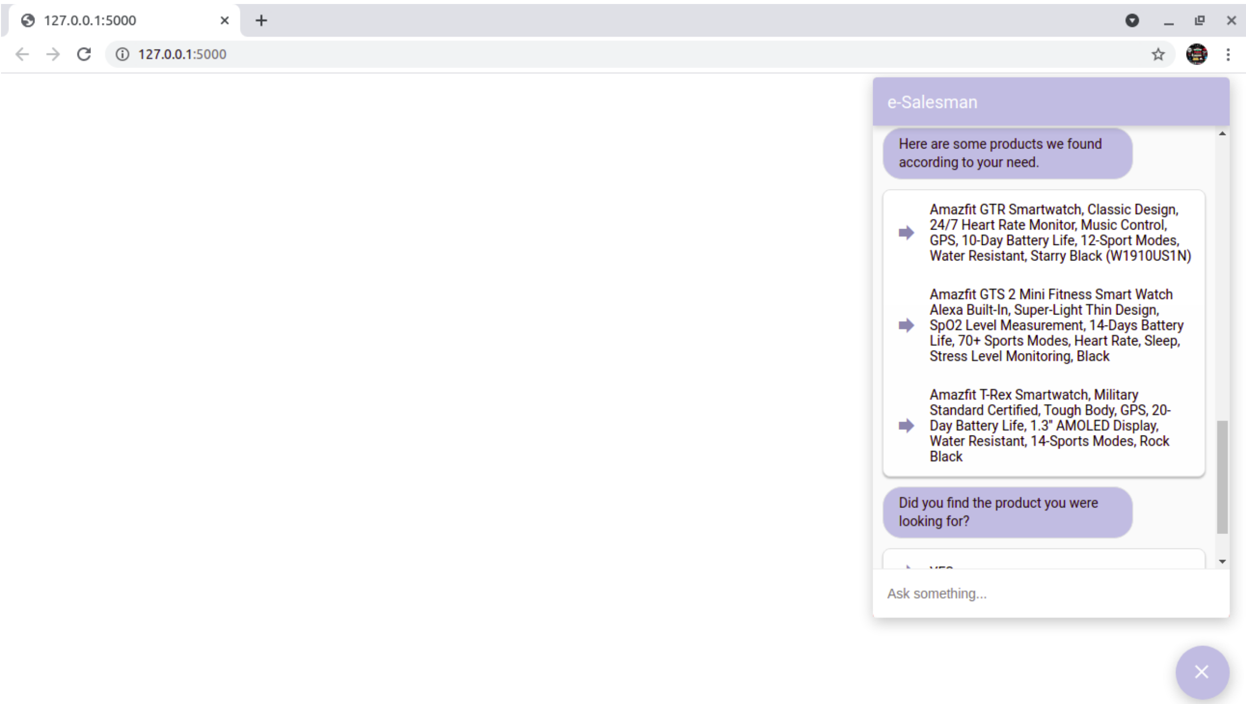

Figure 6.7: Display Product Links

If user is not satisfied, we ask if the user wants to see the bestsellers for the brand in the category he selected.

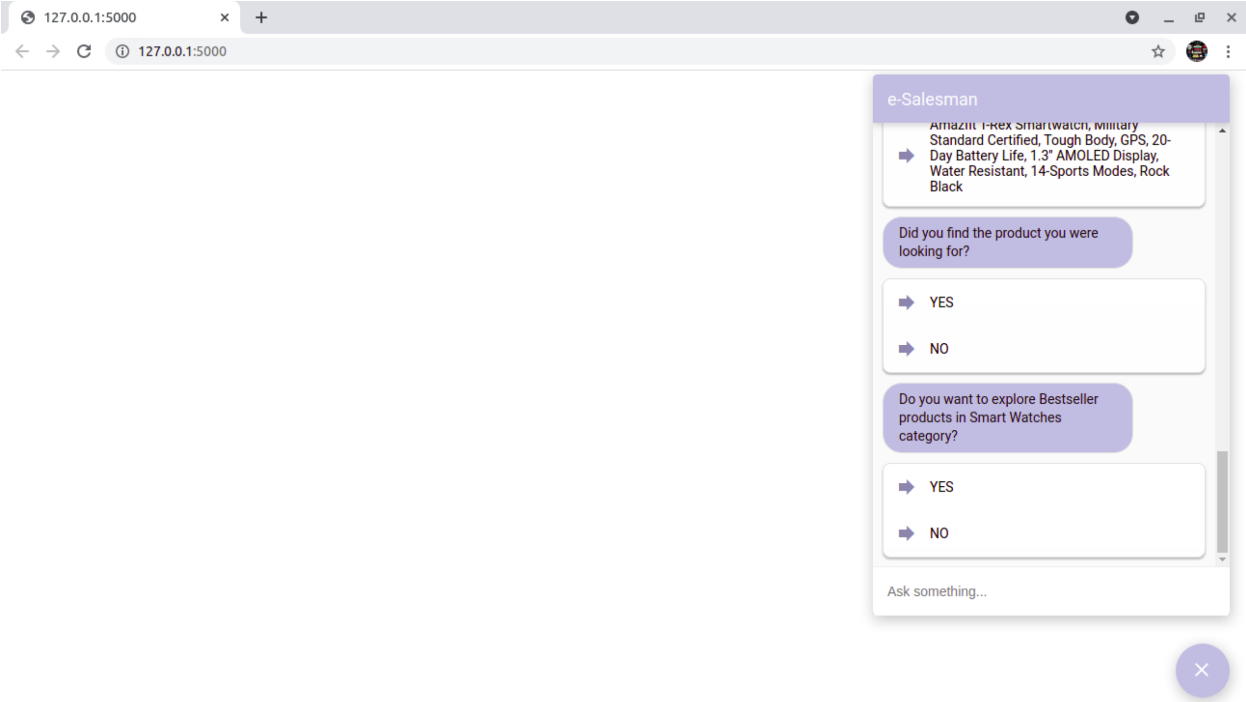

Figure 6.8: Product Bestseller Option

If the user clicks "Yes", we display the top sellers (based on ratings) in the category for the brand user entered.

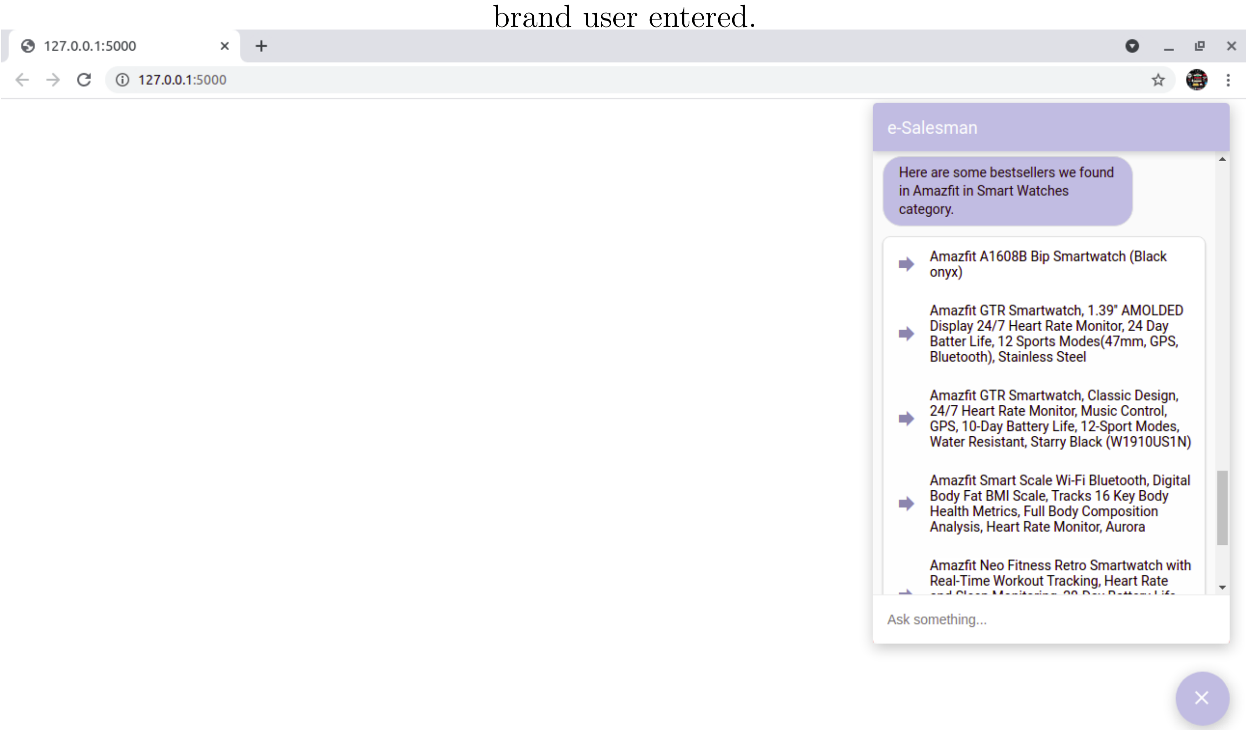

Figure 6.9: Display Bestseller Links

And then we ask the user whether the bestsellers helped him to take a decision(Product Recommendation Feedback). After clicking on any of them buttons (”Yes”/”No”), will lead to the Session End feedback.

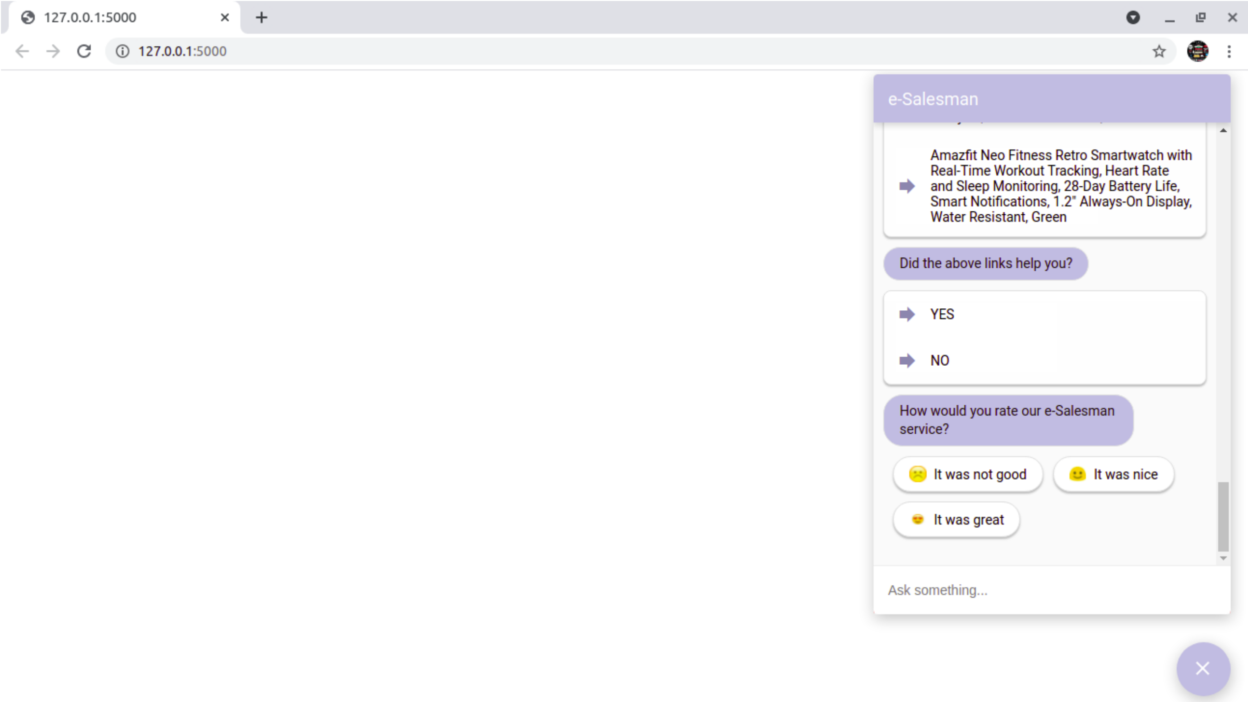

Figure 6.10: Product Recommendation Feedback

After giving the Session End feedback, session ends.

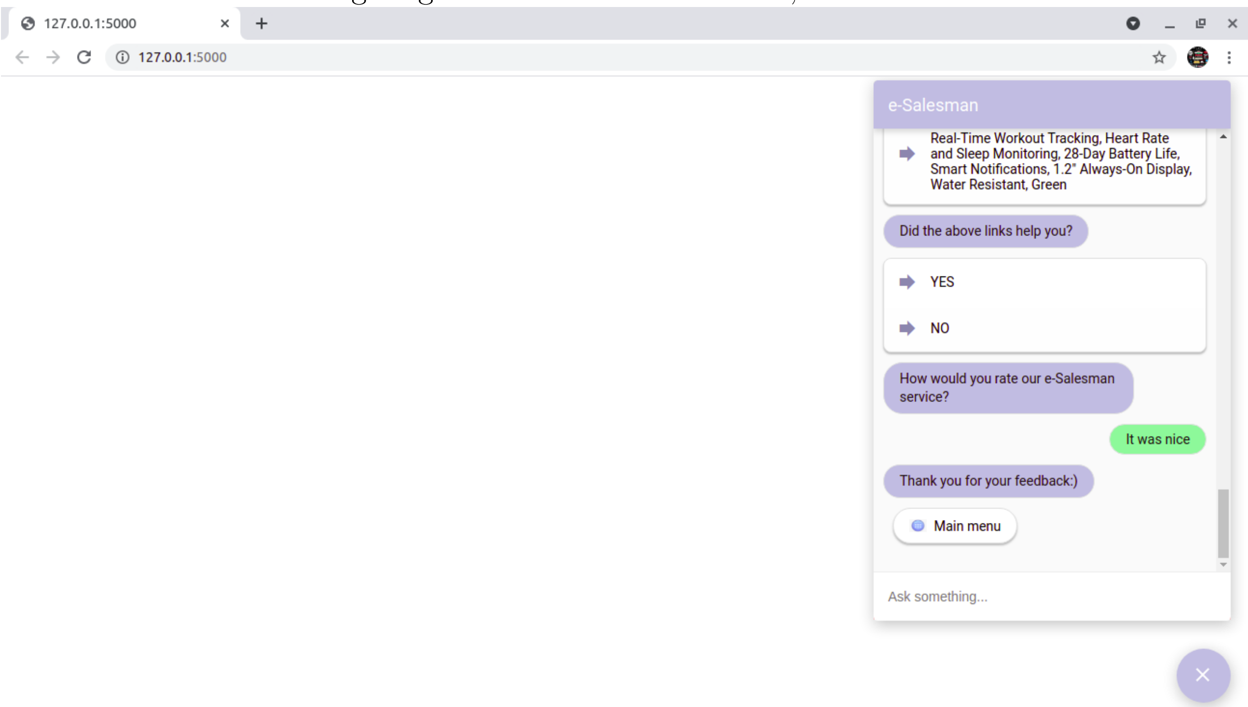

Figure 6.11: Session End Feedback

6.2 Comparison with existing e-commerce chatbots

We have found a chatbot for e-commerce business named as XeroChat Ecommerce Chatbot on messenger. The Chatbot architecture is very alike to our designed e-salesman chatbot and the workflow is also very close to our design, hence we have chosen it for comparing performance of our chatbot functionally. These comparisons are listed below with supporting events.

1. UI : In XeroChat, the product categories are listed horizontally, so the user have to scroll horizontally to see all categories which leads to poor UI experience and usability, whereas we have added chips for product categories vertically. As a result user can see all the product categories available at one glance.

2. Specificity : In Xerochat, the product categories are not further subdivided. We have added subcategory to every category to narrow down the search of the user.

3. User Requirement : XeroChat is not asking for product features and showing direct results of available products without doing any requirement analysis of what the user wants. We are collecting all the required features that are needed to provide the closest results to the user requirement.

4. Sales conversion : Xerochat doesn't ask for price range whereas we take an idea of user's budget and filter the results according to price range leading to more sales conversion.

5. Influencing the decision : In XeroChat the bestseller products are shown as trending products but these products are not mentioned under specific categories rather they are randomly listed. We have given option to get

bestsellers if the user doesn't get satisfied with the results provided in the respective category. This can also be used to influence the choice of the user.

6. Feedbacks, Followups : XeroChat doesn't ask for feedback at any stage while conversing; whereas we are continuously asking followup questions to the user, and formulating chatbot's next response based on the user's response.

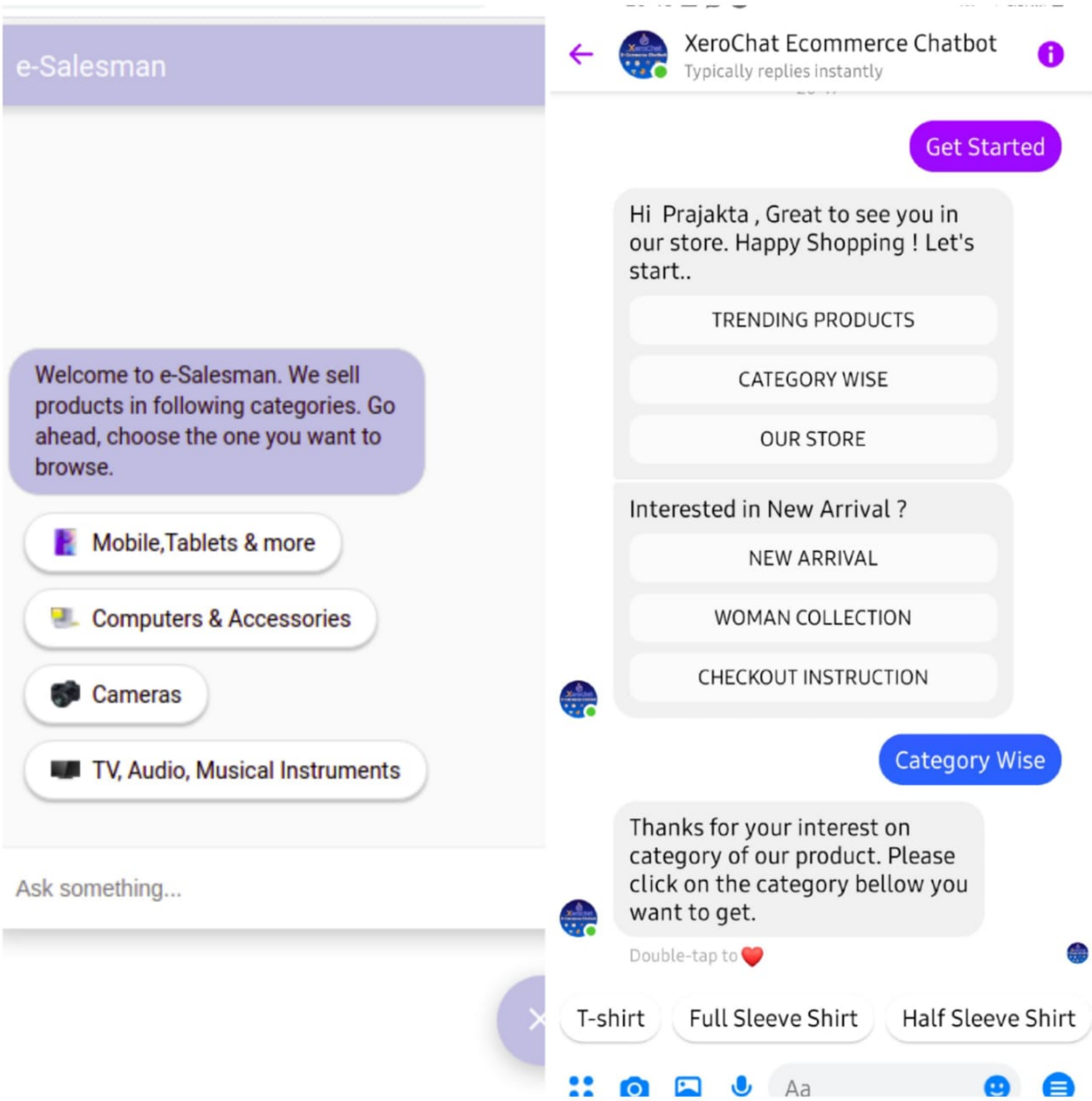

Figure 6.12: Welcome page and View Categories Comparison

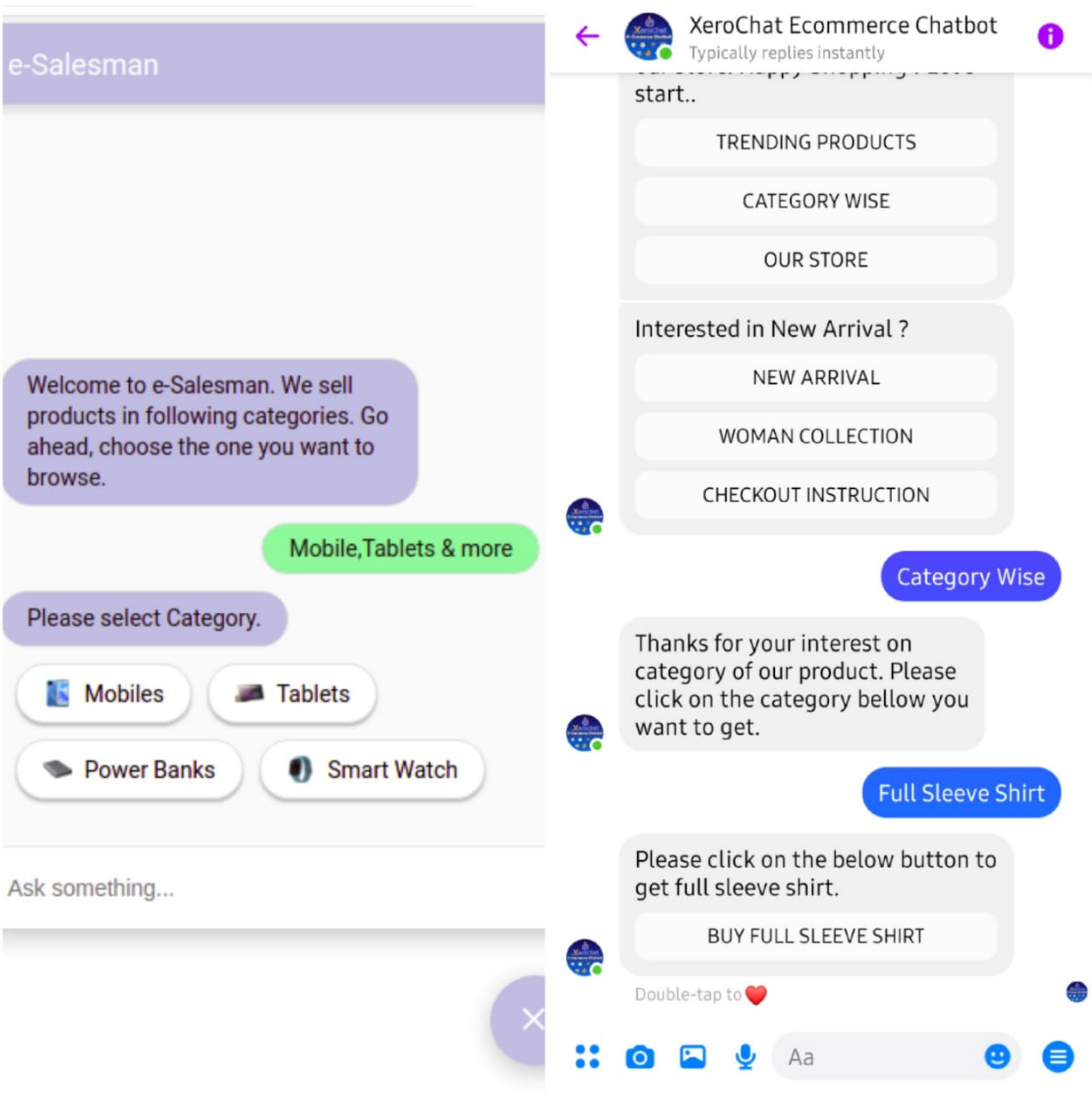

Figure 6.13: View Subcategories Comparison

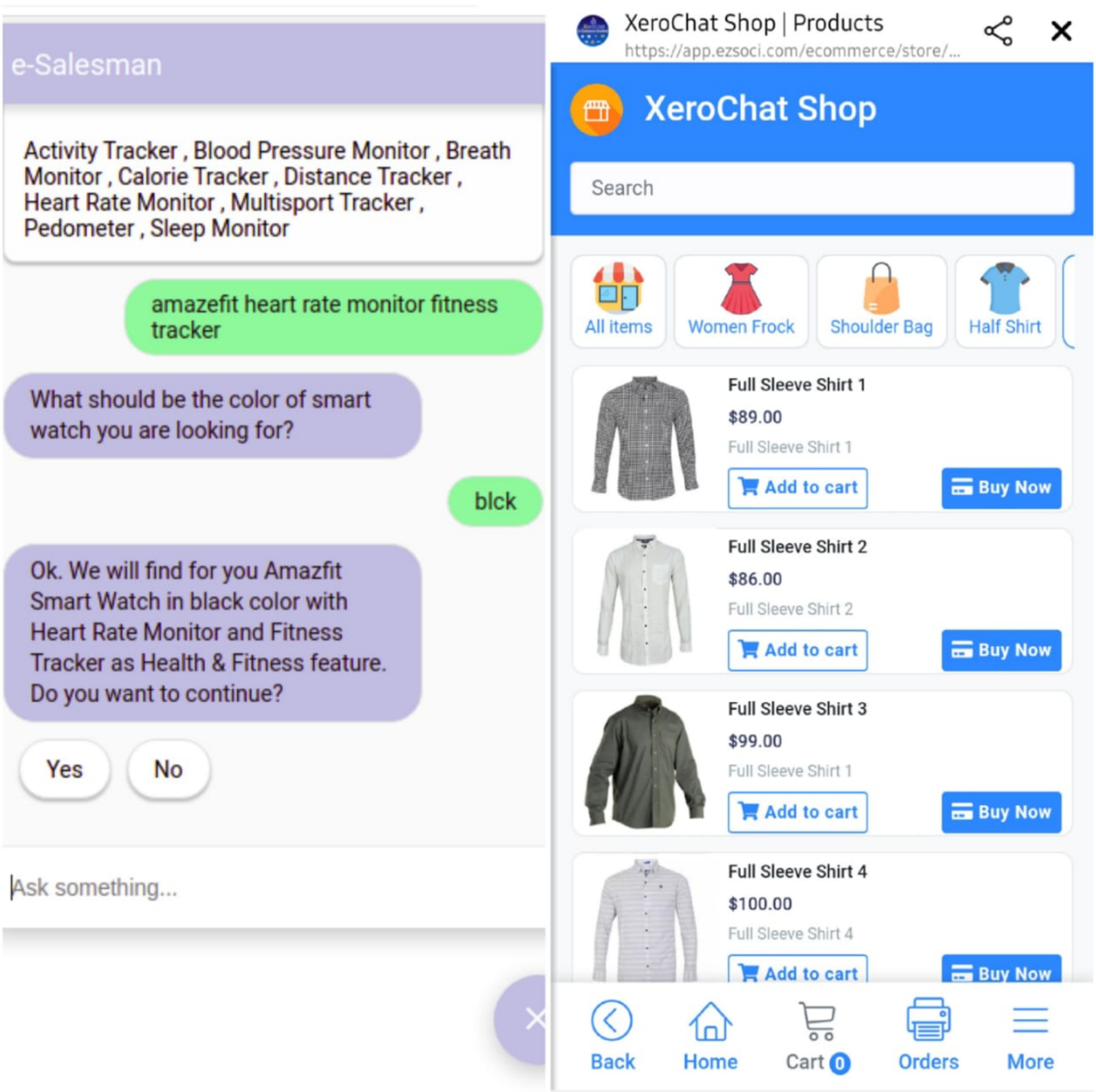

Figure 6.14: Feature Extraction Comparison

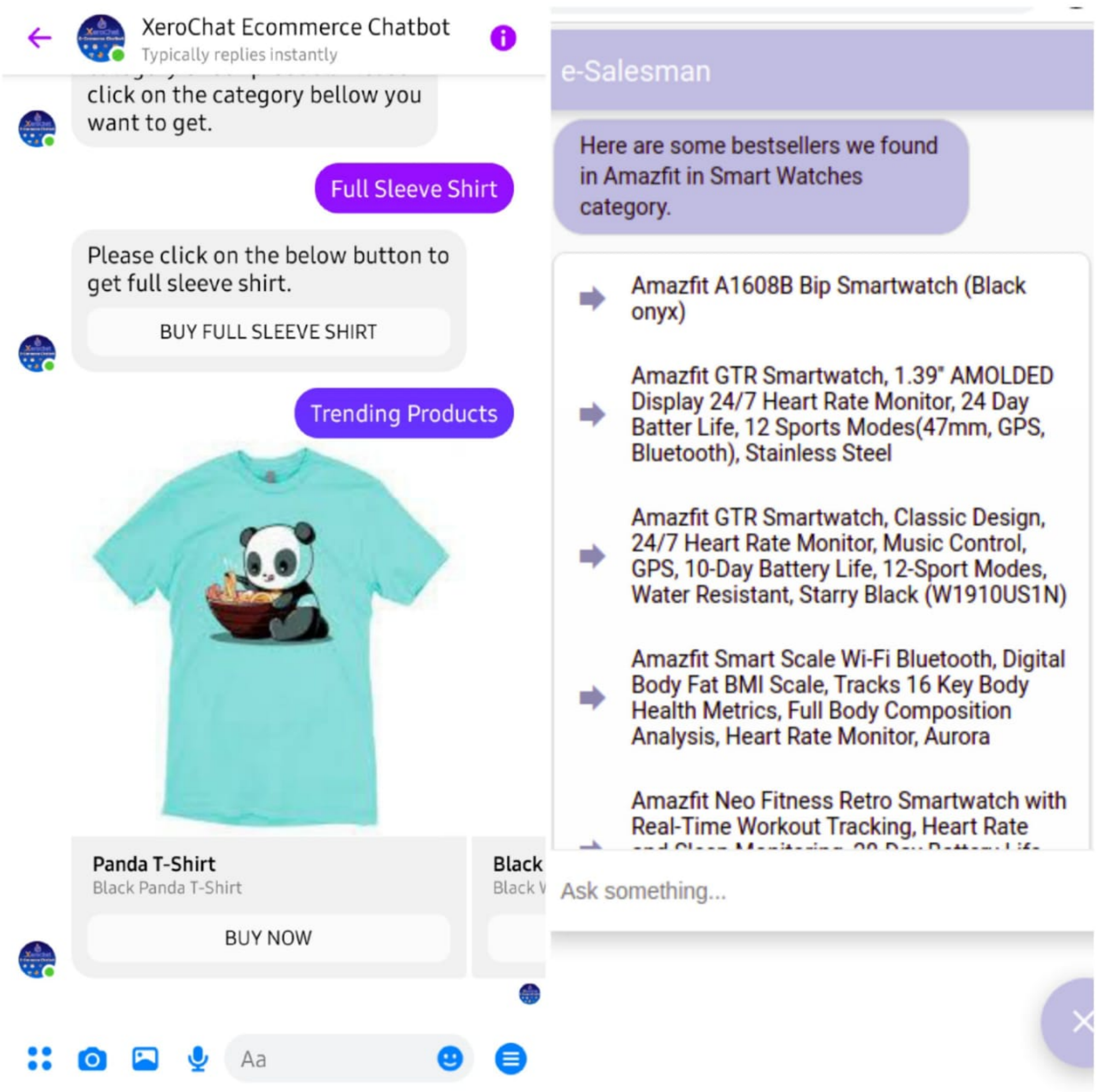

Figure 6.15: Bestsellers Comparison

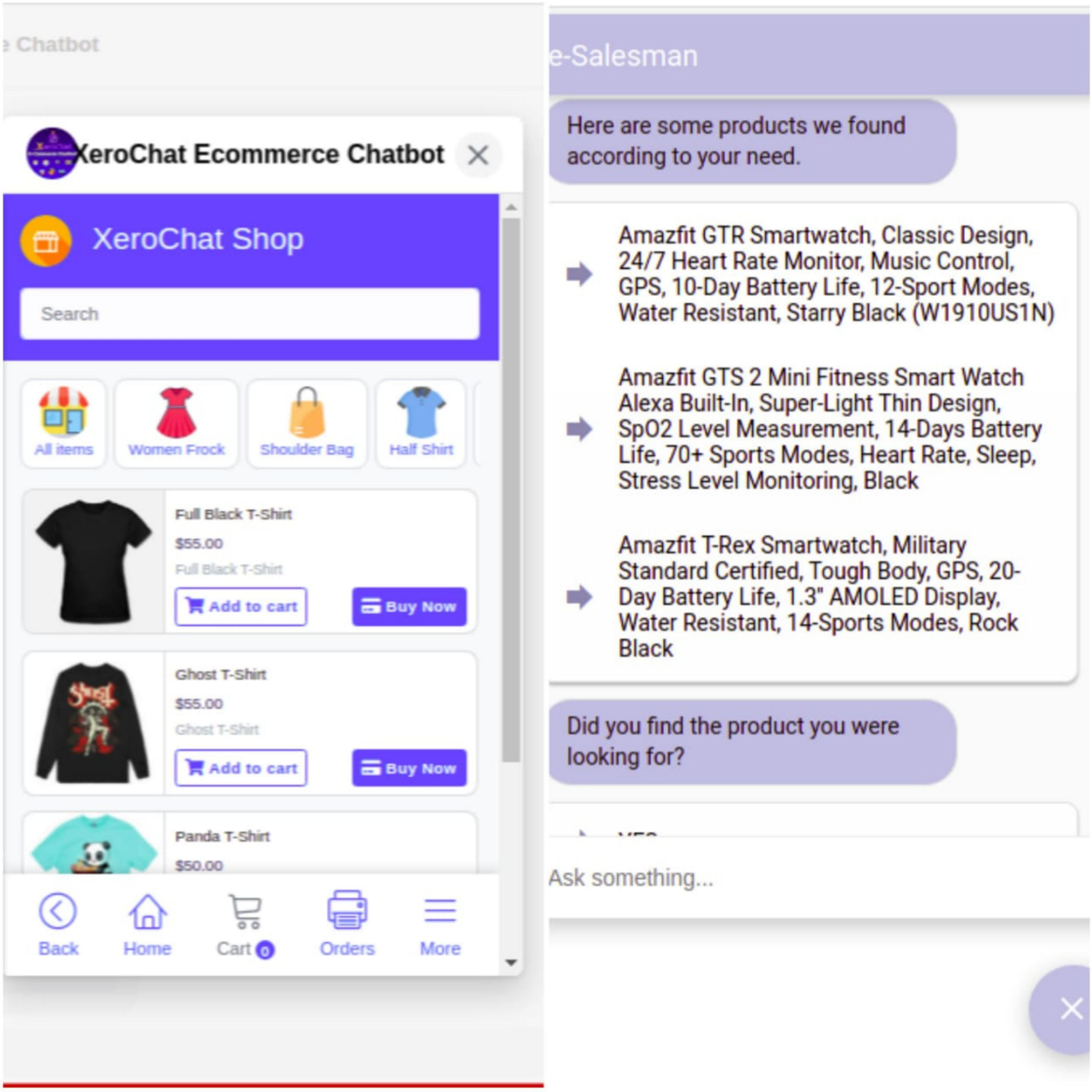

Figure 6.16: Final Search Results and Feedback Comparison

Chapter 7

Conclusion

7.1 Challenge

We studied the problem statement and did literature review based on e-commerce chatbot along with their scopes, design techniques, shortcomings etc. As we came across different shortcomings of existing design techniques for e-commerce chatbot, covering the scope where these shortcomings were removed was a challenge for us.

- Scraping the data from the website like Amazon which doesn't allow bots to crawl was a challenge.
- Webhook request timeout of 5 seconds was a challenge because traversing through huge data and formulating the accurate response took more time.
- Controlling the flow of conversation was a challenge, so that chatbot doesn't give unexpected response in the session.

7.2 Solution

- Dataset challenge is solved by scrapping with Selenium Chrome web-driver and python library beautifulSoup.

- Added a followup intent to the main intent. The main intent triggers the processing, while the followup intent formulates the response from the processed data.

- Added suggestion chips, buttons, accordions to guide the user towards the expected input.

7.3 Usability Impact

As we have studied the existing and traditional methods of communicating with customers, the usability impact was low. In our proposed design, we are trying to give high usability to customers through the user friendly UI with all time availability, query solving, recommendations of related products and various product exploration. This can be judged by the End of the Session feedback given by the user. Based on the user feedback (Not good, nice, great) we give a usability score (0, 3, 5)

7.4 Future Scope

- Collecting enough data so that we will be able to provide product links to the user for any combination of feature values entered.

- Speed up the process of traversing through the database.

- Make a provision where the chatbot will be able to save the conversation, analyze and improve his performance by asking some questions to the user after he gives a negative feedback.

- Making the chatbot user specific by creating an account. The responses will be formulated keeping in mind the history of the user.

Appendix A

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