Design Documentation of ShopAssist AI (ShopAssist 2.0)

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Objective

Objective is to enhance ShopAssist AI, taking it to the next level as ShopAssist 2.0. In this we have to leverage the newly introduced 'function calling' feature to create a more streamlined and efficient chatbot to gain valuable experience in conversational AI and contribute to the development of innovative AI solutions.

Here are the tasks involved:

- Integrate Function Calling API: Modify the existing architecture to leverage the Function Calling API's
 capabilities for improved performance. Scope out which layers can be removed and how the existing
 layers can be updated to handle the new approach.
- **Refine Conversation Flow:** Enhance the chatbot's conversation flow by leveraging function calling. Make the interaction between the user and the chatbot more natural and dynamic.

Project Background

In today's digital age, online shopping has become the go-to option for many consumers. However, the overwhelming number of choices and the lack of personalized assistance can make the shopping experience daunting. To address this, we have developed ShopAssist AI, a chatbot that combines the power of large language models and rule-based functions to ensure accurate and reliable information delivery.

Problem Statement

Given a dataset containing information about laptops (product names, specifications, descriptions, etc.), build a chatbot that parses the dataset and provides accurate laptop recommendations based on user requirements.

Approach

- Conversation and Information Gathering: The chatbot will utilize language models to understand and generate natural responses. Through a conversational flow, it will ask relevant questions to gather information about the user's requirements.
- 2. **Information Extraction:** Once the essential information is collected, rule-based functions come into play, extracting top 3 laptops that best matches the user's needs.
- Personalized Recommendation: Leveraging this extracted information, the chatbot engages in further
 dialogue with the user, efficiently addressing their queries and aiding them in finding the perfect laptop
 solution.

System Design

Dataset: We have a dataset laptop.csv where each row describes the features of a single laptop and also has a small description at the end. The chatbot that we build will leverage LLMs to parse this Description column and provide recommendations.

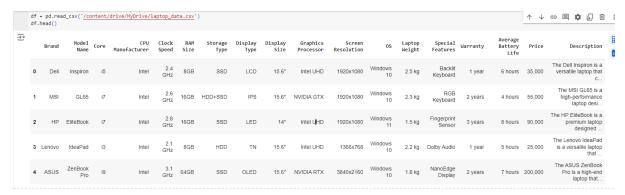


Figure: Sample laptop dataset

Here's the overall flow of conversation for the ShopAssist Chatbot:

The chatbot should ask a series of questions to

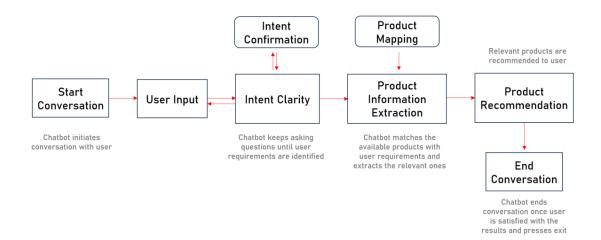
- 1. Determine the user's requirements. For simplicity, we have used 6 features to encapsulate the user's needs. The 6 features are as follows:
- 2. GPU intensity
- 3. Display quality
- 4. Portability
- 5. Multitasking
- 6. Processing speed
- 7. Budget
- 8. Confirm if the user's requirements have been correctly captured at the end.

After that the chatbot lists down the top 3 products that are the most relevant and engages in further conversation to help the user find the best one.

Building the Chatbot

Now let's go ahead and understand the system design for the chatbot.

CHATBOT SYSTEM DESIGN



1. Stage 1

- Intent Clarity Layer
- o Intent Confirmation Layer

2. Stage 2

- o Product Mapping Layer
- o Product Information Extraction Layer

3. Stage 3

o Product Recommendation Layer

Major functions behind the Chatbot

Let's now look at a brief overview of the major functions that form the chatbot. We'll take a deep dive later

- initialize_conversation(): This initializes the variable conversation with the system message.
- get_chat_completions(): This takes the ongoing conversation as the input and returns the response by the assistant
- moderation_check(): This checks if the user's or the assistant's message is inappropriate. If any of these is inappropriate, it ends the conversation.
- intent_confirmation_layer(): This function takes the assistant's response and evaluates if the chatbot
 has captured the user's profile clearly. Specifically, this checks if the following properties for the user
 has been captured or not GPU intensity, Display quality, Portability, Multitasking, Processing speed,
 Budget

- dictionary_present(): This function checks if the final understanding of user's profile is returned by the
 chatbot as a python dictionary or not. If there is a dictionary, it extracts the information as a Python
 dictionary.
- compare_laptops_with_user(): This function compares the user's profile with the different laptops and come back with the top 3 recommendations.
- initialize_conv_reco(): Initializes the recommendations conversation

Implementation

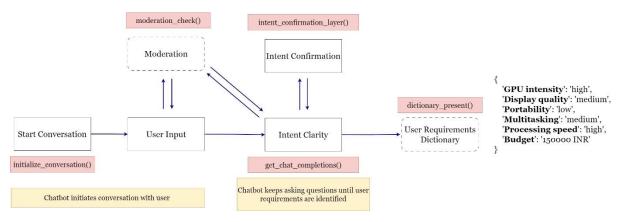
Stage 1+ Stage 2 + Stage 3

Let's start by importing the libraries that we'll require for this project. Following are the ones:

- openai
- pandas
- os, json, ast

Implementing Intent Clarity and Intent Confirmation Layers

Stage 1:



Let's start with the first part of the implementation - building the intent clarity and intent confirmation layers. As mentioned earlier, this layer helps in identifying the user requirements and passing it on to the product matching layer. Here are the functions that we would be using for building these layers:

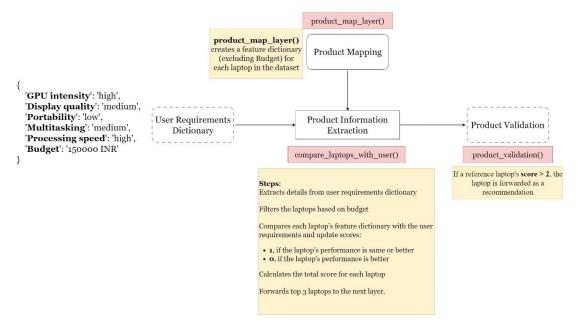
- initialize_conversation(): This initializes the variable conversation with the system message. Using prompt engineering and chain of thought reasoning, the function will enable the chatbot to keep asking questions until the user requirements have been captured in a dictionary. It also includes Few Shot Prompting(sample conversation between the user and assistant) to align the model about user and assistant responses at each step.
- get_chat_model_completions(): This takes the ongoing conversation as the input and returns the response by the assistant
- moderation_check(): This checks if the user's or the assistant's message is inappropriate. If any of these is inappropriate, you can add a break statement to end the conversation.

You need to understand the user's profile, which essentially means that all the features: GPU intensity, Display quality, Portability, Multitasking, Processing speed, Budget are captured or not. Let's look at the function that helps us verify that.

- intent_confirmation_layer(): This function takes the assistant's response and evaluates if the chatbot has captured the user's profile clearly. Specifically, this checks if the following properties for the user has been captured or not
- GPU intensity
- Display quality
- Portability
- Multitasking
- Processing speed
- Budget
- dictionary_present(): This function checks if the final understanding of user's profile is returned by the
 chatbot is a Python dictionary or not. This is important as it'll be used later on for finding the right
 laptops using dictionary matching.

Implementing the Product Mapping and Information Extraction Layers

Stage 2:



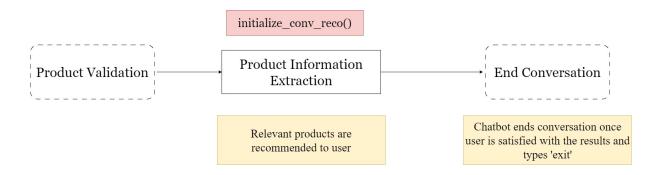
In this section, we take in the output of the previous layers, i.e. the user requirements, which is in the format of a Python dictionary, and extract the top 3 laptop recommendations based on that. Here are the functions that we will use to help us implement the information extraction and product matching layers

• product_map_layer(): This function is responsible for extracting key features and criteria from laptop descriptions. Here's a breakdown of how it works:

- Uses a prompt that assign it the role of a Laptop Specifications Classifier, whose objective is to extract
 key features and classify them based on laptop descriptions. Provide step-by-step instructions for
 extracting laptop features from description.
- Assign specific rules for each feature (e.g., GPU Intensity, Display Quality, Portability, Multitasking, Processing Speed) and associate them with the appropriate classification value (Low, Medium, or High).
- Includes Few Shot Prompting(sample conversation between the user and assistant) to demonstrate the expected result of the feature extraction and classification process.
- extract_dictionary_from_string(): This function takes in the output of the previous layer and extracts the user requirements dictionary
- compare_laptops_with_user(): This function compares the user's profile with the different laptops and come back with the top recommendations. It will perform the following steps:
 - It will take the user requirements dictionary as input Filter the laptops based on their price, keeping only the ones within the user's budget.
 - o Calculate a score for each laptop based on how well it matches the user's requirements.
 - Sort the laptops based on their scores in descending order.
 - Return the top 3 laptops as a JSON-formatted string.

Product Recommendation Layer

Stage 3:



Finally, we come to the product recommendation layer. It takes the output from the compare_laptops_with_user function in the previous layer and provides the recommendations to the user. It has the following steps.

- 1. Initialize the conversation for recommendation.
- 2. Generate the recommendations and display in a presentable format.
- 3. Ask questions basis the recommendations.

Dialogue Management System

Bringing everything together, we create a diagloue_mgmt_system() function that contains the logic of how the different layers would interact with each other. This will be the function that we'll call to initiate the chatbot

Areas of Improvement and Final Comments

You can see that for gamer, the model is not able to perform well. But for the academic and business persona, it is able to perform well.

Future Scope of Work

The output format of each layer is inconsistent. You can use the function API capability of GPT to instruct the output format as per the input request.

- 1. The rule framework provided to classify each laptop's specification is not exhaustive. You can expand the rules to give a comprehensive context to the LLM.
- 2. There are misclassifications in the laptop's specifications, even after specifying clear rules for LLM. You can fine-tune an open-source LLM to make its understanding & performance better.
- 3. Once the products are extracted, the dialogue flow doesn't allow recalling of product extraction if there is any intent change. You can add another layer to observe any request for a change in the user intent and then use this flag to recall the product extraction based on the updated intent.
- 4. As an alternative & simple solution, you can use vector embeddings of each product and compare it with the user intent to find the most relevant products.
- 5. You can template this workflow/solution to build a chatbot for any product domain.

Note: You must add the relevant domain expertise/rules to give the LLM context understanding.