ShopBot

for earphones and headphones

Project Report



|  |  |
| --- | --- |
| **Team Members** | |
| Shashank Nigam | A0198469A |
| Lin Wenqi | A0198435R |
| Ng Mei Ying | A0198546L |
| Edmund Leow Kwong Wei  **TEAM MEMBERS**  Edmund Leow Kwong Wei  Ng Mei Ying  Wilson Lum Kok Keong A0198478A  M A S T E R O F TECH N O L O G Y  P R O J E C T R E P O RT    T E A M M E M B E R S  Edmund Leow Kwong Wei - 1  Ng Mei Ying - 2  Wilson Lum Kok Keong - 3  M A S T E R O F TECH N O L O G Y  P R O J E C T R E P O RT    T E A M M E M B E R S  Edmund Leow Kwong Wei - 1  Ng Mei Ying - 2  Wilson Lum Kok Keong - 3 | A0198458H |

Contents

[1 Executive Summary 1](#_Toc35955037)

[2 Business Problem 1](#_Toc35955038)

[3 Solution Approach 2](#_Toc35955039)

[3.1 Approach and Objective 2](#_Toc35955040)

[3.2 Datasets 2](#_Toc35955041)

[3.3 System Architecture 3](#_Toc35955042)

[4 Chatbot Design 4](#_Toc35955043)

[4.1 Chatbot Personality 4](#_Toc35955044)

[4.2 Intent Classification and Entity Recognition 4](#_Toc35955045)

[4.3 Intents 4](#_Toc35955046)

[4.3.1 Product recommendation 4](#_Toc35955047)

[4.3.2 Explanation of terminology 4](#_Toc35955048)

[4.3.3 Product pricing 4](#_Toc35955049)

[5 Challenges and Limitations 4](#_Toc35955050)

[5.1 Heroku Deployment 4](#_Toc35955051)

[6 Test Results 5](#_Toc35955052)

[7 Conclusions 5](#_Toc35955053)

[8 References 5](#_Toc35955054)

# Executive Summary

TODO

# Business Problem

In today’s world, traditional shopping is declining year-on-year, while e-commerce has been rising and is expected to reach 2.05 billion buyers globally by 2020 [1]. This has led to a much greater variety of products at lower prices, as multiple sellers across different countries compete for a slice of the market [2].

However, in a bid to differentiate their products, retailers often advertise their features with marketing jargon that adds to consumer confusion [3]. In addition, with the plethora of online marketplaces [4], even after deciding on the “best item” item, the consumer needs to decide which platform has the “best” price. All these factors result in consumer confusion and decision paralysis, where consumers experience greater anxiety and stress, and sometimes “buyers’ regret” after purchase, fearing that they have not chosen the “best” possible product [5, 6]. Overwhelmed with choices and decisions, they may even delay or stop shopping all together [7].

In particular, there has been a surge in demand for headphones in the last few years. More than one million headphones were sold per day in 2018 and sales are expected to increase by two-fold in 2024 [8]. Consumers are no longer content with standard earphones that are bundled with mobile phones or MP3 players, and headphones and earphones have become lifestyle accessories for the trendy. Confronted with a large variety of product models, consumers may not always understand the different specifications or find it tedious browsing through countless items to find the product that best suits them.

# Solution Approach

## Approach and Objective

The project objective was to build a product recommendation chatbot for headphones and earphones to give users better “decision simplicity” in their shopping. The main intents are summarised in *Table 1*, and will be discussed in detail in *Chatbot Design*.

Table 1. Chatbot intents and descriptions

|  |  |
| --- | --- |
| Chatbot Intent | Description |
| Product recommendation | Select suitable products according to rating and sentiment in product reviews, as well as, product features deemed important to user (eg long battery life, suitable for sports, etc) |
| Explanation of terminology | Shortlist typical terminology and store the terms into a lookup table; if exact term is not found, word similarity between query and keys would be performed and closest match will be returned. |
| Product pricing | Webscrape prices from Amazon periodically (eg weekly/daily), and display price and website link to purchase in chatbot |

The most natural way for interaction would be through a conversational interface to converse with users and identify their needs, just like what a shop assistant would do.

## Datasets

Several datasets would be utilised for this project. For “Product recommendation” intent, the Amazon Review Data (2018) which contained reviews from 1996 to 2018 **Invalid source specified.** as well as reviews of headphones and earphones from Amazon extracted from webscraping were used for sentiment analysis and also to obtain the list of available products to recommend. For “Explanation of terminology” intent, several websites were web-scraped to obtain a glossary of terminologies. For “Product Pricing” intent, Amazon website was web-scraped for price and delivery costs based on the list of products that were shortlisted in “Product Recommendation”.

The list of dataset sources is summarised in *Table* 2.

Table 2. Dataset sources and usage

|  |  |  |
| --- | --- | --- |
| Purpose | Dataset source | Dataset type |
| Sentiment Analysis | Amazon Reviews (2018) dataset from  <https://nijianmo.github.io/amazon/index.html>  Headphone and earphone reviews from Amazon | Text |
| Information extraction | Product review websites | Text |
| Aspect extraction | Headphone and earphone reviews from Amazon | Text |
| Topic modelling | Headphone and earphone reviews from Amazon | Text |
| Short-listing of products | Shopping websites (Amazon, Qoo10, Lazada, etc)  Review websites | Text,  product IDs |
| Explanation of terminology |  | Text |
| Product Pricing | Amazon Website | Prices |

## System Architecture

The chatbot was hosted on [DialogFlow](https://dialogflow.com/) due to its ease of setup and wide integration with multiple platforms including Google Assistant, Slack and Facebook Messenger. However, intent classification and entity recognition were performed by [Rasa NLU](https://rasa.com/docs/rasa/nlu/about/), as it allowed greater customisation in terms of processing and training. Facebook Messenger, a popular communication platform with good chatbot support, was used as the front end for our chatbot.

When a user enters a message into the chatbot platform, its API sends the message to DialogFlow. Instead of using DialogFlow’s NLP engine to process all intents and entities, we utilised it for only basic categorisation and sent the raw input to our flask webhook app for preprocessing and then forward it to Rasa NLU model to determine intents and entities. The appropriate response is formulated in the flask app and then returned to the user.

Ideally, for deployment, the Flask app and Rasa NLU server should be hosted in Heroku server. However, there were several problems in doing so[[1]](#footnote-1), and finally for this prototype, it would be assumed that the Flask app and Rasa NLU server would be ran locally, and exposed to the internet with a public url provided through ngrok.

# Chatbot Design

This section discusses the different aspects of our chatbot design, including chatbot persona, entities, intents and conversation flows.

## Chatbot Personality

Our target audience will be mainly young people within the age range 18-34., as these were deemed to be the people that had the highest chance of intending to purchase earbuds within the next 12 months [9].

There are 12 archetypes commonly used to define a brand persona, which are functionally identical to the 12 Jungian archetypes [10]. As our target audience are young people, we will stereotype them as Explorers, who are ambitious and always seek out new things. In order for them to identify well with our bot, we will mirror the personality of our audience [11] and also give it the same archetype Explorer, with a friendly, energetic and enthusiastic personality. This will be projected in its interactions with our users. For example, when returning the price for a specific item, it might respond with something like “Woohoo! It’s your lucky day! 🤩 You can get this for $100, with free delivery from Amazon! Here’s the link: …”

In coming up with a name, it was important that we had a memorable name that was linked to our core business of earphones and music, so that our users could easily remember it. We came out with AudioPhil, as a play on the word “audiophile”, who is a person who is enthusiastic about high-fidelity sound reproduction. Phil is also uncommon enough while being an easy name to remember.

In coming up with an avatar picture, we wanted the users to have reasonable expectations of our chatbot. It was found that consumers expected chatbots to behave like human agents but wanted it to be clear that they are bots [12]. In addition, if the chatbot was too convincing as a human, people were more likely to speak quickly and less clearly, and have higher expectations for the system [13]. Hence, we adopted a cartoon-like avatar so that they will know immediately that it was a bot. At the same time, we wanted it to appear friendly, hence we opted for a human avatar. Since our chatbot is supposed to be like a virtual shop assistant, and since we recommend headphones, so we also added headphones on him.

With all these in mind, our final chatbot persona is given in *Figure 1*.

|  |  |  |
| --- | --- | --- |
| **AudioPhil** | **Interests and Passions**   * Listening to music * Audio history and latest technology in headphones * Trying out the newest headphones on the market * Helping people find their ‘headphone soulmate’   **Quotes**     |  | | --- | | Hello there! I am Phil. Let’s work together to discover the perfect headphones for you today! | |
| **Friendly • Energetic • Attentive** |
| **Age**: 20  **Occupation**: Earphone Purchase Specialist  **Location**: Singapore  **Archetype**: Explorer (ENTP) |

Figure 1. Chatbot Persona

## Intent Classification and Entity Recognition

Basic natural language processing (NLP) was first carried out using DialogFlow. However, it had several major limitations such as (i) unable to perform customised preprocessing and processing of inputs, and (ii) unable to easily input a large list of training and test phrases. Hence, we adopted a hybrid approach, where intents and entities were defined within DialogFlow, but processing for intent classification and entity recognition were done by Rasa.

This allowed us to adopt the following preprocessing pipeline for user inputs as shown below. By performing such preprocessing, we simplified the training examples that were required (eg. No need to consider Singlish; no need to consider both singular and plural tenses, etc).

|  |
| --- |
| Raw input 🡪 remove singlish end-words (eg la, lo, etc) 🡪 strip punctuation and convert to lowercase 🡪 perform stemming 🡪 Processed input. |

Training example datasets were generated using a third-party tool [Chatito](https://github.com/rodrigopivi/Chatito), by defining examples in a custom domain specific language (DSL), which simplified the generation of samples. A snippet of the chatito file used to generate training samples for “Explanation of terminology” is given in *Figure 2*. From the simple definitions below, training and testing datasets could be easily generated by iterating and permutating through the different combinations that were defined.

In order to streamline our workflow, a script (\_generate\_lookup\_files.py) was also created to generate lookup tables for the entities of the intents, as well as to add these to the chatito file that would be used to generate training and testing examples.

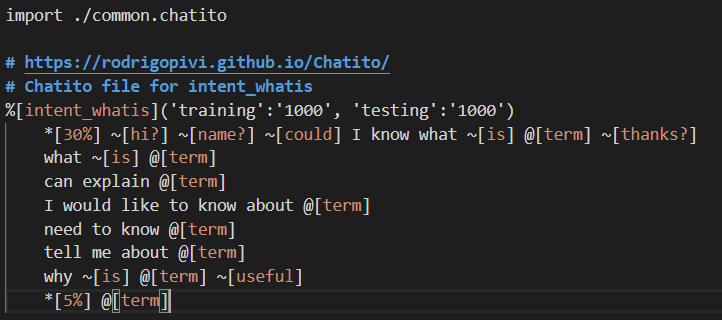


Figure 2. Example snippet of chatito file

In Rasa NLU, incoming messages are processed by a sequence of components that will executed one after another in a so-called processing pipeline. The three main parts are (i) tokenization, (ii) featurization and (iii) entity recognition/intent classification/response selectors[[2]](#footnote-2).

In order to determine the best pipeline, various NLU pipelines were compared and it was found that the following pipeline gave good results for our dataset.

TODO

## Intent Details

### Product recommendation

TODO

### Explanation of terminology

TODO

### Product pricing

We decided to use the product list from Treoo.com as opposed to Amazon.com. This was because being a local site, any products found in its website was guaranteed to be available, and delivery cost need not be calculated (we will assume self-collection, which is free). In comparison, products in Amazon could be from multiple sellers, in different conditions (new or used), different delivery cost (free or not, and if not, price differed greatly depending on type of delivery).

However, using the Treoo product list was not trivial. Unlike Amazon which had a unique identifier for each product (ASIN), in Treoo there was nothing like this, and product name was very inconsistent. Some inconsistencies, using AKG models as examples, are shown in *Table 3*. Therefore, various pre-processing methods had to be done to standardise them.

Table 3. Example inconsistencies in Treoo product names for AKG brand

|  |  |
| --- | --- |
| **Example** | **Comment** |
| AKG K52 | Ideal format |
| AKG K 545 | Extra space between K and 545 |
| AKG K845BT Wireless Bluetooth Over-the-Ear Headphone | Features are also included in the description |

For Treoo, there was a total of 144 brands and 1643 different models. Visualising it in a network graph (each node denotes a brand, and size of node shows number of models in a brand) and barplot, we can see that there are actually many brands with only a few models. In order to simplify and reduce considerations, brands with less than 5 models were filtered away and the rest were used to generate a lookup table of brands and their models.

|  |  |
| --- | --- |
|  |  |

# Test Results

TODO

# Challenges and Limitations

We encountered several issues with DialogFlow, Rasa NLP, and Heroku deployment while working on the chatbot and will elaborate on them in the following subsections.

## Heroku Deployment

TODO

# Conclusions

TODO

# References

|  |  |
| --- | --- |
| [1] | Oberlo, “Find out How Many People Shop Online in 2020,” [Online]. Available: https://www.oberlo.com/statistics/how-many-people-shop-online. |
| [2] | “The growth of e-commerce means more choice and better deals,” The National, 2 Jan 2018. [Online]. Available: https://www.thenational.ae/opinion/editorial/the-growth-of-e-commerce-means-more-choice-and-better-deals-1.692313. |
| [3] | R. Carter, “Lost in translation: The dangers of marketing jargon,” Fabrik Brands, 1 Aug 2019. [Online]. Available: https://fabrikbrands.com/the-dangers-of-marketing-jargon/. |
| [4] | “The biggest online marketplaces that you should know,” IONOS, 6 8 2019. [Online]. Available: https://www.ionos.com/digitalguide/online-marketing/online-sales/the-biggest-online-marketplaces-that-you-should-know/. |
| [5] | B. Schwartz, The paradox of choice : why more is less, New York: Ecco, 2004. |
| [6] | L. M. Lyengar S, “When choice is demotivating: Can one desire too much of a good thing,” *Journal of Personality and Social Psychology,* vol. 79, pp. 995-1006, 2000. |
| [7] | Knowledge@Wharton, “Online Shopping Choices: Less Is Sometimes Better Than More,” Wharton University of Pennsylvania, 17 Dec 2013. [Online]. Available: https://knowledge.wharton.upenn.edu/article/online-shopping-choices-less-sometimes-better/. |
| [8] | A. A. &. Intelligence, “Global Earphones and Headphones Market to Reach Values of $36 Billion During the Period 2018−2024,” PRNewswire, 14 Feb 2019. [Online]. Available: https://www.prnewswire.com/news-releases/global-earphones-and-headphones-market-to-reach-values-of-36-billion-during-the-period-20182024--market-research-by-arizton-300795642.html. |
| [9] | T. O. Team, “The State of Play 2019: What’s next for audio tech,” Qualcomm, 5 Sept 2019. [Online]. Available: https://www.qualcomm.com/news/onq/2019/09/05/state-play-2019-whats-next-audio-tech. |
| [10] | N. Smith, “Does Your Brand Have Multiple Personality Disorder? A Look at Brand Archetypes,” nvision designs, 10 November 2015. [Online]. Available: http://www.nvision-that.com/design-from-all-angles/what-is-your-brand-personality-a-look-at-brand-archetypes. |
| [11] | T. Manifest, “How to Give Your Chatbot a Personality,” 11 Dec 2018. [Online]. Available: https://chatbotslife.com/how-to-give-your-chatbot-a-personality-5e0fb239b28c. |
| [12] | Leah, “What Do Your Customers Actually Think About Chatbots?,” Userlike, 30 Jan 2019. [Online]. Available: https://www.userlike.com/en/blog/consumer-chatbot-perceptions. |
| [13] | K. Waddell, “Chatbots Have Entered the Uncanny Valley,” The Atlantic, 21 Apr 2017. [Online]. Available: https://www.theatlantic.com/technology/archive/2017/04/uncanny-valley-digital-assistants/523806/. |
| [14] | V. MacMillan, “How to Develop a Chatbot Persona That Fits Your Brand,” Medium, 26 April 2018. [Online]. Available: https://chatbotslife.com/how-to-develop-a-chatbot-persona-that-fits-your-brand-c48055970372. |
| [15] | T. F. Tay, “Tourist arrivals, spending in Singapore at record highs,” Straits Times, 14 February 2019. [Online]. Available: https://www.straitstimes.com/singapore/tourist-arrivals-spending-at-record-highs. [Accessed 28 August 2019]. |

1. See *Challenges and Limitations* [↑](#footnote-ref-1)
2. See <https://rasa.com/docs/rasa/nlu/choosing-a-pipeline/#understanding-the-rasa-nlu-pipeline> for details [↑](#footnote-ref-2)