

# Calibre ChatBot

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## ABSTRACT

Ever since there has been a trend of chatbots in the commercial sector, there has been a wide deployment in the customer service sector. In the ultimatum, these chatbots can not respond to queries unless there is a database provided. Contrastingly, generative chatbots try to formulate the most relevant response, but are mostly unable to create a smooth functioning in the customer- bot interaction.

Chatbots are increasingly being used in business sectors and is often being replaced by customer care services. Unfortunately, basic task oriented chatbots are unable to address client enquiries that are not present in their Frequently Asked Questions (FAQ) dataset. We will employ Natural Language Processing (NLP) technology to construct a conversational chatbot that can speak more robustly with its clients. It will help solving a wide range of queries and presenting the customer with occasional prompts. This shall make the customer-chatbot conversation more natural and promote brand royalty

We have built a chatbot for Calibre which is a gaming shop. It finds the underlying objective of the customer's query by matching similar patterns in the intents. To measure the model's performance we have used performance metrics such as Precision, Recall and F1 Score.

## I. INTRODUCTION

Gaming stores are rarely open throughout the week 24/7, thus their sales and timings are fixed. Even though the website can be used anywhere anytime, it is not practical for one to satisfy everybody's queries and demands. Also, enhancement of customer care that is more employees for resolving queries can be practically impossible for small startups. To avoid this, employment of chatbot on Calibre's website can help customers solve their queries regarding the shop and its details at any place and time. This can aid customer experience since their queries are resolved within a snap. This also can help not lose their

customers and save and in fact increment their sales. Most of the chatbots that we see on the websites are limited to certain keywords and queries. They are called rule-based chatbots. This means it would be unable to respond if there is a new pattern or new queries since it works on certain sets of rules and previously saved patterns. Hence, making the rule-based chatbots primary can not be implementable. Using NLP and Machine Learning(ML), we implemented a responsive and fully-functioning chatbot which not only helps with customer issues but also recommends the users about the latest gaming hardware and software. It also has the capability to generate questions which can follow up after the user has invoked a conversation , making the experience more human and lively.

The image depicts how contrasting the two different bots provide help.

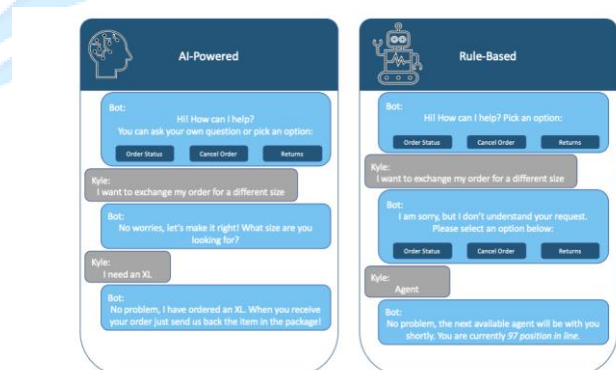


Figure 1: Rule-based vs AI-based Chatbots

2. Digitalization of companies has been observed on a large scale. E-commerce companies are resorting more towards chatbots to save employee costs. Furthermore, they hope to create experience of sales in a more personalized and efficient manner. A chatbot not only does provide solutions to the questions of consumers but also provides product recommendations focusing on the user's interest. Moreover, sentiment and semantic analysis, recall

and precision has been helpful in crafting personalized experience. In the year 2022, it had been observed that 88 percent of the users had at least one or more conversations with a chatbot. 52 percent of organizations found an increase in usage of automation and 86 percent of users said AI has become one of the ‘mainstream tech’.

### 3. Background

Automated chat agent relays in natural language with its users. They can be classified into two classes:

- a) Task-oriented dialog agents: These ensure the fulfillment of the foundation role of adhering to the given queries or replying to inquiries on websites.
- b) Chatbots: These are invoked in such a way that they can understand extended and unstructured conversations. They can be functional for both entertainment and query handling efficiently ..

The two basic types of chatbots that are Rule-based and AI based chatbots are easier and harder to implement respectively. Rule-based chatbots are simpler, having limited capabilities. They provide an answer on the basis of their previously saved patterns and can therefore, produce faulty or no solutions. Unlike Rule-based agents AI- based models can easily understand the user intent and context. It also uses negative feedback to improve its performance.

AI based chatbots have two further categories, namely Information Retrieval(IR) chatbots and Generative chatbots. Information Retrieval chatbots are trained on textual dataset and provide predefined answers based on existing data or databases. They rely on keywords and intent matching to decipher user enquiries. This knowledge base for this type of model is usually formed using a database of query-answer pairs which can be fast.

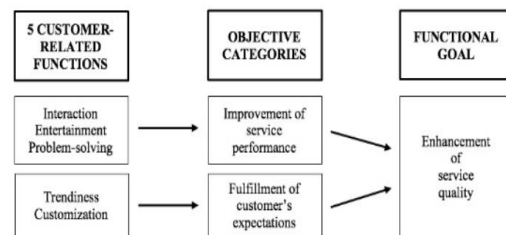
Generative Models generate new sentences from scratch based on queries from the user. However, their dataset has to be trained which can contain a lot of phrases and real conversations. This can affect the accuracy but overtime by training the model continuously it can improve. The model learns sentence structuring and vocabulary while aiming for correct and accurate answers.

Neural Networks which were introduced in late 1980’s are large computational networks that are trained on huge datasets in order to approximate some complex target function. They are computational systems that try to resolve problems like a human brain, and hence can be used to solve

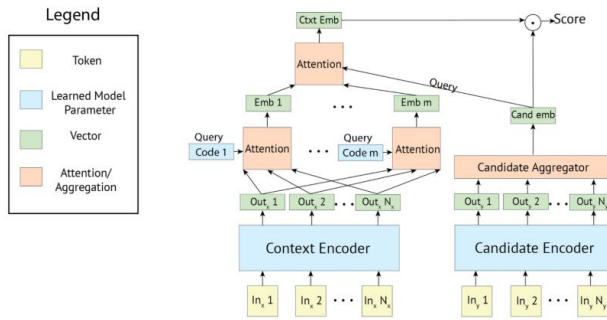
problems like natural language understanding and intent classification.

### II. THEORETICAL FRAMEWORK

The term “chatbot” is a portmanteau word which resembles the verb “chatting” and the noun “robot“. It can also be described as conversational software with the power of simulating human communication skills. Natural Language Processing is used to carry out real-time communication with the aim of conversing with the user. Usually unanswered queries result in the need to contact customer care, which faces a lot of issues such as long waiting times, inflexible working hours and inexperienced staff. This makes users embark on a journey of frustration and hatred towards the website. Lack of support, social interaction and personal advice of the employees can be factors to why customer care is not a recommendable option. However, blending both customer service with the facility of chatbot can provide the best combination to improve one's conversion rate and analytics. Chatbots provide convenient and interactive alternatives to customer care. A chatbot is always ready to offer 27/7 support and its mood is completely unaffected. Overall , regardless of whether a FAQ-answer, product information regarding,a price or a contact, chatbot has it all and can provide accurate answers without venturing towards customer support.



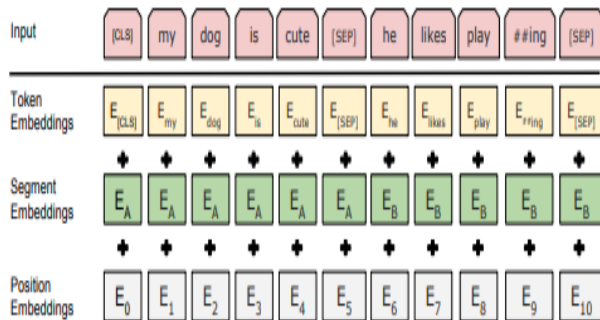
Out of all the problems ,it has been found out that 37% of the problems can be solved through Chatbot. Whether issues arise while searching or search enquiries or other complaints, the chatbot’s support is available anytime for the user’s service. Chatbots actively identify keywords in a customer’s requests and evidently provide best answers. After every use, the database from which the information is extracted is then updated and enlarged at the same time helping future user’s to face faster and improved details. Therefore all of these factors combined together can form a chatbot as a powerful solving tool in customer service context.



### III. MODEL ARCHITECTURE AND METHODOLOGY

Sentiment analysis is a methodology used in natural language processing to help models understand the human innate nature and notions better and more accurately. Our paper explores the different directions this concept can be expanded to and the future possibilities it entails. A multitude of language models like RoBERTa use sentiment analysis techniques which help improve the accuracy and reduce validation loss. Some of the metrics used are F1, recall and precision.

To decipher the complex version of it and get more accurate results, we also experimented with learned parameters and aggregation concepts.



#### A. Traditional Machine Learning Models:

Early sentiment analysis models often relied on machine learning algorithms such as Support Vector Machines (SVM), Naive Bayes, and Logistic Regression. These models typically utilized handcrafted features such as n-grams, part-of-speech tags, and syntactic patterns to capture sentiment information.

We developed the chatbot in three different ways:

1. For our first method, we built the chatbot based on TensorFlow’s Keras Sequential model -a feed forward multi-layer neural network. The customer’s input enquiry is processed and then is compared with the “patterns” or “queries” in our self-generated customer service

dataset. The pre-processing steps include tokenizing, stemming, lemmatization and removing punctuation from our dataset. The input and output layers of the Neural Network consist of One-Hot-Encoded (OHE)

embeddings to describe patterns and predicted intents respectively. During the model’s feed forward pass, it optimizes the layer weights using Stochastic

Gradient Descent (SGD) and has a standard learning rate

of 0.01. The model uses the Rectified Linear Unit (ReLU) as

the activation function between outputs and inputs of adjacent

hidden layers. At the last layer, Softmax is applied to our multinomial linear regression model to normalize the output layer results.

2. In the second method, the embeddings from One-HotEncoding were replaced by embeddings generated by SentenceTransformer model. This was done to observe how naive One-Hot-Encoded embeddings and the more meaningful SentenceTransformer embeddings of size 384x1 would affect the classifier model’s predictions.

3. In the last method, the SentenceTransformer model from the

previous variation was used, but the Intent Classification Model was replaced with a Cosine Similarity Function. This function determines the pattern from the corpus to which the input customer query is most similar. The intent of the matched pattern is extended to the input and the query is assigned its tag. Finally, a response and optional followup is generated as mentioned above.

Following is an example of the final method’s working:

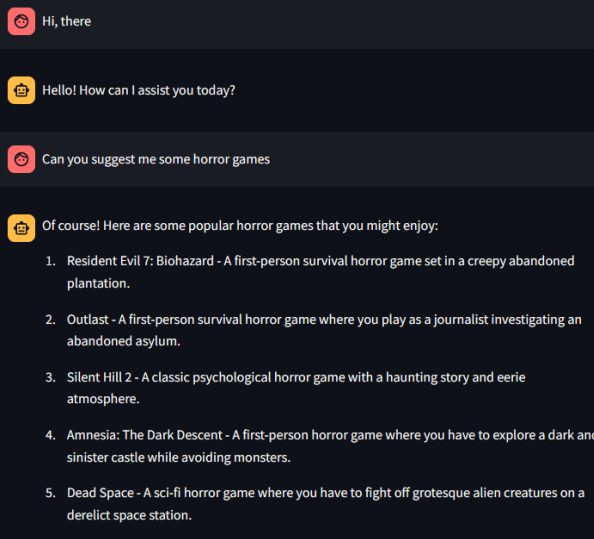
Input Query: What games are the best?

Matched Pattern: What is the best game?

Predicted Intent: game

Response: The best game is Fortnite..

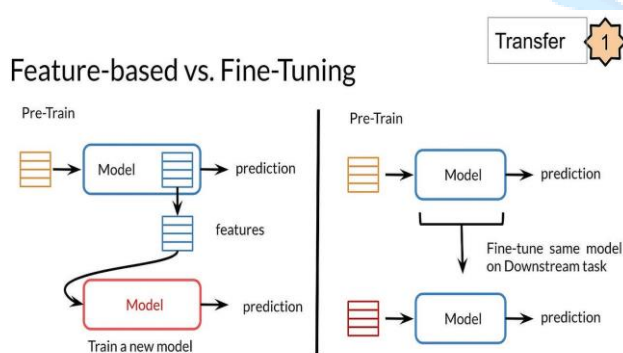
## Caliber Chatbot



### IV. FINE TUNING

Our model is fine tuned using the latest data processing and optimization frameworks and concepts. It has been trained for over 100 epochs for better performance and learning with an accuracy of 0.8.

The model has been trained on a custom dataset with over a 100 gaming related questions. These questions consist of a multitude of games and suggestions, along with user queries and demands. They help the model understand more empathetically about what the user desires as an answer.



#### A. Chatbot and customer service

The usability of a chatbot goes hand in hand with the ramifications of the diverse roles it performs. Customer satisfaction, accountability and quick resolution of queries are some of the actions they perform.

Chatbot can answer questions about the purchase of some products and what is most bought. The fact that the chatbot is 24/7 available and accessible can give this an upper hand over normal customer service

which includes long waiting times and may also lead to frustration of customers since there is an inclusion of personal advice given regarding the query. It remains unbiased unlike customer care when asked for recommendations of products almost instantaneously. Chatbots are highly efficient in handling multiple queries simultaneously, making sure that customer management is done even at the neck of the moment. Chatbots with the help of sentimental analysis can decipher what emotion the customer is trying to convey, whether it be anger or sadness, the chatbot gives a response according to the customer's situation. Moreover, chatbots can provide real-time highlights and tries to keep updating itself after each and every query.

### V. SENTIMENT ANALYSIS

Calibre chatbot consists of optimization techniques and concepts aiding in improving the accuracy score and validation loss. It helps categorize questions and answers into labels customized for the project. It can help analyze the emotions and opinions expressed in the flow of the conversation. Sentiment analysis in chatbots uses Natural Language Processing and Machine Learning algorithms to analyze text data and determine the polarity of the sentiment. Lexicon based analysis, Naive Bayes, Support Vector Machines and Neural Network is widely used. Sentimental polarity has different polarities:

1. Positive Sentiment : Expression of satisfaction, happiness and approval.
2. Negative Sentiment : Expression of sadness, anger and dissatisfaction.
3. Neutral Sentiment : Expression of neutrality, confused and lack of strong emotion

### VI. PERFORMANCE METRICS

Performance metrics helps in calculating the accuracy scores of the model using metrics like F1 score, recall and precision. Play a crucial role in evaluating the overall effectiveness and accuracy of the model. These scores consist of understanding the feasibility of using POS tagging, stopwords etc.

$$\text{precision} = \frac{tp}{tp + fp}$$

$$\text{recall} = \frac{tp}{tp + fn}$$

$$\text{F1-score} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

## VII. ACCURACY

Calibre chatbot has achieved accuracy of 80% over a custom dataset. Accuracy is the fundamental performance metric which is used to calculate the chatbot's functionality and how well it works..

With an neu score of 0.22, it showcases how the validation loss is so little and thus, giving more accurate results.

```
y_pred_binary = [1 if pred == true else 0 for pred, true in zip(y_pred, y_true)]
y_true_binary = [1] * dataset_size

accuracy_percentage = accuracy_score(y_true_binary, y_pred_binary) * 100

print(f"Accuracy: {accuracy_percentage:.2f}%")
```

Accuracy: 80.00%

```
PS C:\Users\soman\chatbot\python-command-line-chat-gpt> python score.py
[nltk_data] Downloading package vader_lexicon to
[nltk_data] C:\Users\soman\AppData\Roaming\nltk_data...
[nltk_data] Package vader_lexicon is already up-to-date!
{'neg': 0.0, 'neu': 0.222, 'pos': 0.778, 'compound': 0.7901}
F1 Score: 0.8571428571428571
Precision: 1.0
Recall: 0.75
```

## IV. FUTURE WORK

Even though our system works well for most of the queries, the knowledge domain is constrained to a small dataset. However, we can expand it by adding more intents, patterns and responses. Additionally, run-time and live price calculations can be a supplementary feature to our bot. Implementation of Recommendation System can give rise to a huge boost to the application. Lastly, these unidentified intents could be dynamically inserted into the corpus to decrease the number of scrapings required.

Future prospects for this experiment include the use of RNNs, double decoder Transforms and GANs. .

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