Chatbot

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Business Problem

Time is money, and there is a tradeoff for value of the product and the level of service received. While top notch service has a concierge feel, that level of delivery is not always practical. In our fast-paced world clients are looking for on demand service. To support the balance of timely service and expense, chatbots are utilized to optimize data enablement. Chatbots are computer programs that simulate human conversation through text or phone interactions. This tool allows end users to find information more independently and efficiently while reducing expense for the organization. (Gills, 2024)

Background/History

The first meaningful version of the chatbot emerged in 1966 called ELIZA. It utilized a parroting effect by repeating words back to the person according to a template. PARRY was developed similarly in 1968 with emotional enhancements added.

The first supervised learning bot wasn't developed until 1995, called A.L.I.C.E. This led to the first voice interaction chatbot with Jabberwacky in 1997. Mitsuku arrived in the early 2000s but wasn't award-winning until 2013. Mitsuku still continues to win awards for its ability to continue genuine and emotionally intelligent conversations with humans (see Appendix for ELIZA and Mitsuku conversations) (Codecademy Team, n.d.).

Data Explanation

I am using a JSON file from Data Flair that contains categories as well as pre-defined pattern and responses. There are fourteen categories labeled as "tag". These tags are focused on general greetings, closings, and health related topics.

Figure 1

Example of a JSON tag.

```
{"tag": "greeting",
 "patterns": ["Hi there", "How are you", "Is anyone there?","Hey","Hola", "Hello", "Good day"],
 "responses": ["Hello, thanks for asking", "Good to see you again", "Hi there, how can I help?"],
 "context": [""]
```

The tags are greeting, goodbye, thanks, noanswer, options, adverse_drug, blood_pressure, blood_pressure_search, search_blood_pressure_by_patient_id, pharmacy_search, search_pharmacy_by_name, hospital_search, search_hospital_by_params, search_hospital_by_type.

Methods

I created a retrieval based chatbot through data preprocessing, modeling, and formulating a graphical user interface (GUI). The model predicts the category that the input belongs to. I created functions to identify the category and retrieve a random response from the list of responses.

I loaded the JSON file into Python and parsed the JSON into three lists: words, classes, documents. I applied preprocessing by tokenizing the words within each pattern. Then, the tokenized works were added to the words list, and the tokenized words were also added with the corresponding tag as a tuple to the documents list. Next, each tag was added to the class list.

I took the words list and lemmatized each word. The words list and classes list were both sorted. Then, all lists were viewed. There were 47 documents, 9 classes and 88 unique, lemmatized words.

When creating the training data, the input and the output was provided. The input is the pattern, and the output is the class that the pattern belongs to. Prior to training the model the text

was converted into numbers in preparation for the model. Bag of words was used to accomplish this.

I trained a recurrent neural network model using a Keras Sequential model with three layers. The first layer had 128 neurons, the second layer had 64, and the third output layer was equal to the number of intents. Dropout layers were also added at 50% as a regularization technique to account for overfitting the model.

Figure 2

Model Summary

Model: "sequential"

Layer (type)	Output Shape
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 64)
dropout_1 (Dropout)	(None, 64)
dense_2 (Dense)	(None, 9)

Total params: 20,235 (79.05 KB)

Trainable params: 20,233 (79.04 KB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 2 (12.00 B)

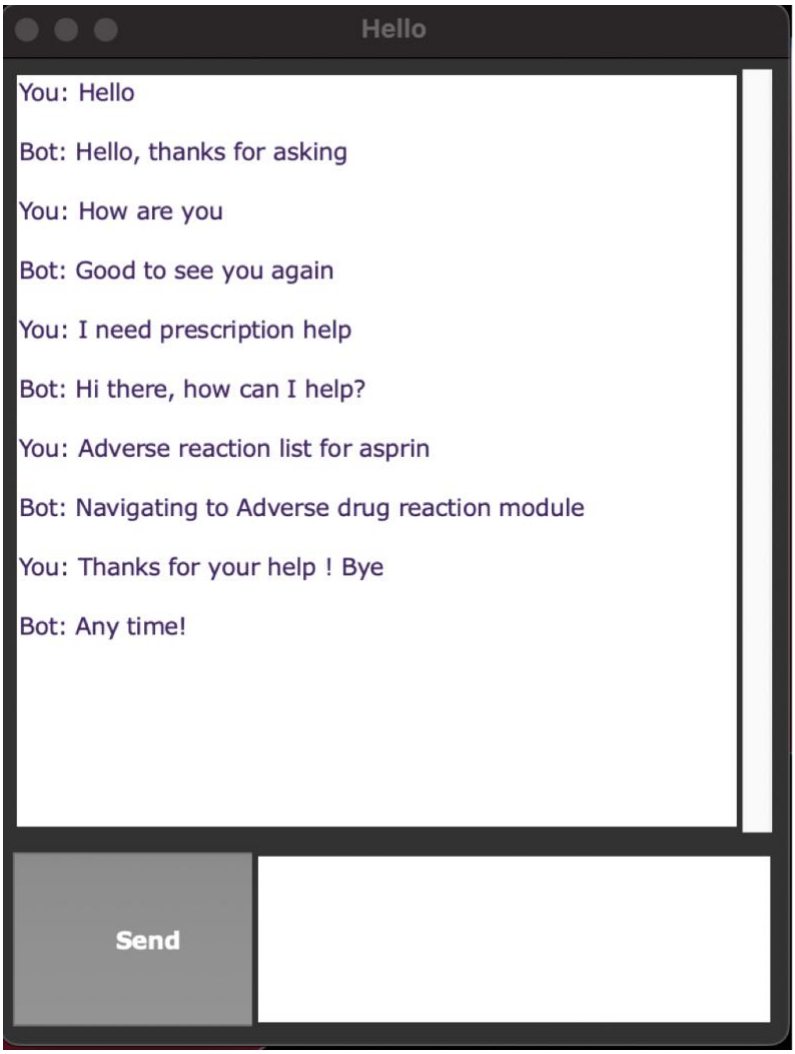
Analysis

When compiling the model, I used sgd for the optimizer, categorical cross entropy for the loss function, and accuracy to evaluate the model's performance. After 200 epochs, the accuracy

score was .9862 with loss of .2027. I created a Graphical User Interface to visualize the chatbot's functionality and execution.

Figure 3

Input and output of the chatbot through the GUI



Conclusion

Organizations are looking for ways to automate workflows and find service solutions that can scale to the masses while minimizing overhead expense. To address this business problem, I

developed a foundational chatbot to provide a first line, on-demand client service solutions. The chatbot leverages deep learning, performs with accuracy, and provides foundational client service support to stay competitive in the marketplace.

Assumptions

When chatbots learn from previous input data, it is assuming what is right. This is why some sort of human intervention is needed to audit responses.

Several assumptions other assumptions to consider when creating chatbots through natural language process modeling are user intent, context understanding, domain knowledge, user behavior, language proficiency, response time, data privacy and security, error handling, learning and adaptation, and integration.

Limitations

This dataset is extremely limited in size and does not account for complex conversational scenarios. However, the structure is foundational and can be built upon. This chatbot is trained on a very specific domain and does not have the capacity at this point to respond to topics outside of its expertise.

Challenges

Language is complex, especially when various languages, emotions, and intentions are involved. It can be a struggle for chatbots to understand these complexities, including spelling errors, slang, or emotional intelligence. Scalability can also be an issue if there are high volumes of simultaneous users.

Future Uses/Additional Applications

With the advancement of chatbot development, chatbots are becoming more intelligent. This is in relation to both artificial intelligence and emotional intelligence. This allows chatbots to be much more humanized.

One advantage of the quick enhancements made to chatbots is the ability to leverage them for day-to-day productivity. That can be suggested schedules, writing code, and much more. Chatbots will make the ultimate virtual assistants.

As voice and emotional chatbot enhancements continue to evolve. I anticipate chatbots being utilized more and more as companions or for counseling.

Recommendations

The dataset needs to be expanded to accommodate more robust end user scenarios. The model can be enhanced utilizing pre-trained word embeddings to capture semantic relationships between words, Named Entity Recognition (NER), or Sentiment Analysis. Different models and hyperparameter tuning can also be explored.

The model needs to be enhanced to account for scalability and performance issues. High volumes of simultaneous users can train the system impacting the user experience. Chatbots are also vulnerable to security breaches. This makes implementing robust safeguards necessary to protect privacy.

Implementation Plan

Clear purpose, objectives, and desired outcomes need to be identified prior to implementation. User acceptance testing needs to be performed, and I also suggest a pilot testing group prior to a full deployment.

Once deployed, end user adoption and metrics need to be monitored. Some key metrics that can be observed to improve the model are average conversation length, number of conversations, number of engaged conversations, number of unique users, missed messages, human takeover rate, goal completion rate, customer satisfaction scores, and average response time. All these analytics need to be visualized in a dashboard view to help identify the most important metrics quickly (Cyca, 2022).

Analytics are impactful once decisions and actions can be made because of the metrics. Dedicated resources need to be in place to monitor metrics and enhance the model timely.

Ethical Assessment

One ethical issue is user consent. End users need to be informed on how data is collected, utilized, and stored. Chatting with a bot on an Amazon order issue is one thing but chatting with a bot over a mental health issue in another. Sensitive or private data may be collected within the chat. This also leads to a data privacy and security concern. If that information is leaked due to a security breach, then it becomes a protected health information issue and could result in mental harm (Coghlan, 2023).

It is also essential that AI chatbots remain objective and do not perpetuate bias. In bias is in the training data, such as racial or gender bias, this can generate biased decisions and responses to the end users (Botbuz, 2023).

With the ease of access to chat bots, it can become a dependency for end users to be reliant on problem solving from chatbots. This limits one's ability to exercise critical thinking skills and collaboration with others which can contribute to both disempowerment and social isolation (Botbuz, 2023).

References

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Appendix

Conversation with ELIZA:

Codecademy: Hey Eliza, what do you want to talk about?
ELIZA: You're not really talking about me -- are you?
Codecademy: I asked you what you wanted to talk about
ELIZA: Do you wish to asked I what me?
Codecademy: I don't understand. What?
ELIZA: Why don't you understand?
Codecademy: Because your question doesn't make sense
ELIZA: What about your own question doesn't make sense?

Conversation with MITSUKU:

Codecademy: hey mitsuku, what do you want to talk about?
MITSUKU: I like to talk about movies, robots and history.
Codecademy: what is your favorite movie?
MITSUKU: My favourite movie is Terminator. Have you seen it?
Codecademy: yeah, I saw it a while ago.
MITSUKU: What's your favorite scene? What did you think about it? What did it look like?
Codecademy: I like the whole thing. I can't just pick one scene out of it. The ending is pretty good though.

(Codecademy Team, n.d)