An Experimental Application of Unsupervised Modeling to Chatbots

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Abstract

Chatbots are computer programs designed to emulate an intelligent conversation that is indistinguishable to what a human could provide. They are used for a multitude of functions from technical assistance to personal companionships. A large variety of these chatbots use large databases with collected hard coded answers or attempt to learn proper answers through some sort of supervised machine learning. These approaches can sometimes create reasonable but unhuman-like responses. We propose to instead use actual human responses derived from Twitter to simulate a more human grammar.

Introduction

Chatbots are used daily around the world for a multitude of tasks. A chatbot is defined by many as a form of artificial intelligence that has the ability to mimic a human-like conversation. This simple idea can easily be implemented to create technical support identities or intelligent personal assistants, and perhaps even for personal companionship. But, to implement a design that can truly be indistinguishable or equivalent to a human is no trivial task.

One of the first known implementations of a chatbot was the program ELIZA. ELIZA was written in MAD-Slip for the IBM 7094. Its name was chosen to emphasize that it may be incrementally improved by its users (Weizenbaum 1966).

Human:	Men are all alike.
ELIZA:	In what way?
Human:	They're always bugging us about something.
ELIZA:	Can you think of a special example?
Human:	Well, my boyfriend made me come here.
ELIZA:	Your boyfriend made you come here?
Human:	He says I'm depressed much of the time.
ELIZA:	I'm sorry to hear that you are depressed much of the time.
Human:	It's true. I'm unhappy.
ELIZA:	Do you think coming here will help you not to be unhappy?
Human:	I need some help, that much seems certain.

Figure 1: An example of a conversation with ELIZA.

ELIZA used keyword mapping, where it searched the input for a word and associated rules with it. Like in the example, the keyword depressed triggers a response of Im sorry to hear that you are depressed. While this may work well in certain instances, if the user was to ask a question, this technique would not work as well. To move away from these hard-coded responses you need to implement a type of machine learning environment. Machine learning will allow the program to learn new words or sentences without the need to hard-code these responses. An example of using a machine learning technique can be found in A.L.I.C.E., Artificial Linguistic Internet Computer Entity.

ALICE was created by Dr. Richard S. Wallace in 2003. While learning, ALICE creates an Artificial Intelligence Mark-Up Language which holds in general three different categories generated by a pattern consisting of words, spaces and wild-card symbols (Wallace 2003). These categories are Atomic, Default and Recursive. A template is generated as a response for each category. The Atomic category holds all patterns that do not include the wild card, while the Default category holds all patterns that do have the wildcard symbols. Finally, the Recursive will hold categories that may be too large to accurately deduce a meaning, and hence need to be shortened into smaller ones. For example, Hello * would be categorized in the Default section and a templated response can be generated as Hi there *.

We will be using this type of categorizing with modification that these templated responses will be pulled from the Twitter API to emulate more real human responses. Using this technique will allow for real-time categorization without the restriction of a permanent, static database. These responses will also reflect the currently used phrases and words. The idea is that while a more ridged response or Template may result in a higher acceptance rate from the user, a dynamically generated response will generate a more human like response that makes it less distinguishable as a computer program.

Related Work

Similar work with was done by Ritter et al. (Ritter et al. 2010). However, Ritter et al. focused more on the tagging of the Twitter conversations with the approach of unsupervised conversation models, where the discovery of acts amounts to clustering utterances with similar conversational roles. The goal of this was to eliminate the collection and tagging process and allow the learning algorithm to categorize how people converse in a new medium.

Banko and Etzioni instead attempted to use entire web-

sites collected as a corpus for use with ALICE. At the beginning of each learning task, ALICE receives an unexplored concept $c(n)$ as input, instantiates the set of extraction patters (e.g such as) with name of $c(n)$, (e.g. fruit such as), applies them over the input corpus, and uses the assessment model to add high-probability instances of $c(n)$ to its theory (Banko 2007). This is beneficial in the fact that it was almost 80% accurate but is not representative of normal speech behavior.

Implementation

We begin by receiving a sentence from a user through a command line interface. In our original strategy, we planned to classify the tweets and the input into one of eight broad categories, namely: Status, Question to Followers, Reference Broadcast, Question, Reaction, Comment, Answer, and Response (Ritter et al. 2010). The goal behind this strategy was to have the chatbot produce more accurate responses by responding to Questions with Answers, for example. However, during the implementation we noticed that strictly enforcing this strategy actually caused our chatbot to become less realistic in some scenarios. This is because, in a real conversation, humans often respond to a question with a question. By restricting the chatbot's responses to particular broad categories, we made certain realistic responses impossible from the outset, and the chatbot was therefore too rigid. Therefore, instead, we now focus primarily on finding a tweet that is relevant to the input, but not what broad category the tweet is in.

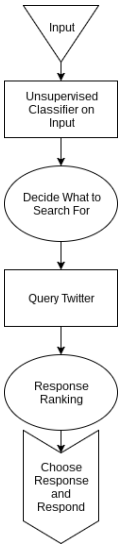

Figure 2: Logic flowchart for our chatbot.

We maintain a continuously updating local database of tweets to use for chatbot responses. The goal of using Twitter tweets as a live corpus is to simulate a more relaxed and realistic conversation, such as what one would find on the Internet. We tried grouping the tweets and the input into similar groups in two different ways. First, we grouped the tweets and the input in an unlabeled way by utilizing the k-means clustering module in the Pattern python library (Smedt and Daelemans 2012). The k-means approach was fairly effective. We would simply use RankReponse on whatever cluster of tweets the input was placed into, thus insuring that the response tweet was relevant to the input. However, k-means took a long time as we increased the number of tweets it could operate on. This was somewhat mitigated by using a smaller value for k and fewer iterations. However, a response using k-means still took a long time.

This prompted us to take a look at another approach to group the tweets and the input, also available through the Pattern library, namely, Latent Semantic Analysis (LSA). This approach creates topics based on what it identifies as important keywords and similar features in all the tweets. It then assigns a probability to each tweet for it being in a particular category. We place the tweets into the category with the highest probability. We then use this result to place the input with tweets in the same topic category. Once the tweets and the user input are grouped into the same topic category, we then rank the relevance of those tweets using our RankResponse algorithm, as we did for the k-means approach. We found that LSA was impressively realistic with the relevance of tweets that it would find, especially when the input contained popular keywords found on Twitter.

```
User:     do you like trump?
Chatbot:  did KellyAnne marry into the Trump family and I just
          missed it?  Yeah, didn't think so…

          (u'trump', 0.09642409227494203)
```

Figure 3: High probability response for 'trump' keyword

Our RankReponse algorithm is as follows. First, we vectorize the user input and each tweet according to word frequency. For example, the following tweet A =“It is a nice day is it not' and input B=“I think it is a nice day” would be vectorized as follows: $c = [\text{i think it is a nice day not}]$, $a = [0, 0, 2, 2, 0, 1, 1, 1]$, $b = [1, 1, 1, 1, 1, 1, 1, 0]$.

We then calculate the cosine similarity $\frac{ab}{|a||b|}$ between each vectorized input and tweet. The tweets are ranked according to cosine similarity, and the tweet with the highest similarity is selected as a response.

RankResponse($tweets, input$)

1: $R = []$ ▷ Initialize our list of responses
2: **for** tweet in tweets **do**
3: $r =$ CosineSimilarity(tweet, input)
4: InsertSorted(r, tweet, R)
5: **end for**
6: return $R[0]$ ▷ The most similar result is returned

Interestingly, since our corpus is based on Twitter, which is known for slang and typos, the chatbot tends to provide more accurate responses when the user input also contains slang and typos, since there is a higher similarity between the user input and the tweets. An example of an informal conversation utilizing slang from our chatbot is below:

```
User:      hi there, i'm chris.
Chatbot:   i'm back & i love it
User:      glad you are happy
Chatbot:   where are you now that i need you
User:      i am home, you?
Chatbot:   i miss you, i miss you, i miss you..
User:      where r u?
Chatbot:   GBC Disaster Relief Training.
           Why r u not trained? What r u waiting on?
```

Figure 4: Sample conversation with our chatbot.

Evaluation Methods

We evaluate the effectiveness of our chatbot both qualitatively and quantitatively. First, to evaluate our chatbot qualitatively, we ask a specific question, and then determine whether the response from the chatbot seemed human-like. This evaluation method obviously necessarily requires a degree of subjectivity, but will nonetheless allow us to judge the relative effectiveness of the chatbot in holding a conversation. In this area, the chatbot performed suprisingly well. Depending on the inputs given, the responses seemed quite relevant. For example, any input including a politician such as Trump receives a remarkably realistic relevant and emotional response. The vagueness of many of the response tweets also helped to keep the conversation open-ended feeling. This is considered a positive by us, since we were aiming for the chatbot to seem less scripted and more natural.

Second, in order to quantitatively evaluate the effectiveness of our chatbot, we adopt a method inspired by Ritter (Ritter et al. 2010). This method will attempt to objectively rate the conversational accuracy of the chatbot in terms of its ability to replicate an actual twitter conversation. In other words, we use a real tweet as input to the chatbot. Then, we expect the response given by the chatbot to be the actual tweet given by a human in a real world conversation. We rate the overall effectiveness of the chatbot by calculating the percentage of conversations it correctly predicted. We consider our chatbot to be a success if it's percentage of correct conversation predictions is near 80%.

Our quantitative evaluations did not go well so far, currently being at 0%. The problem we ran into stemmed from using cosine similarity to rank the final relevance of the tweets. In short, the chatbot would respond with the same exact tweet in the database that we entered as user input due to the 100% similarity of the two. In order to mitigate this problem, we plan on implementing a randomization system that prevents the chatbot from using the same exact tweet as the input, but still a relevant tweet.

Future Explorations

A key advantage to our chatbot approach is that it will more closely mimic real human conversations by including slang and other less formal language available in Twitter messages. However, an obvious downside to our approach is that using real verbatim tweets means that the chatbot's responses will be less personalized. For example, currently, our chatbot cannot refer to its conversation partner by a specific name unless, by coincidence, a real tweet happens to contain that name.

Therefore, a future area of exploration for our chatbot could include modifying its response so that it is not an exact verbatim tweet. For example, if we know that the chatbot is conversing with someone named Bob, we could inject that name in front of the tweet in specific contexts. In order to accomplish this, we would need to ensure that the name injection resulted in a coherent tweet. This would involve more closely analyzing the parts of speech of the response tweet in order to make accurate injections specific to the context of the conversation and sentence structure.

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