A Chatbot to Identify Sentence Ambiguity in Conversational Text

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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ABSTRACT
The use of Affective Computing (AC) in newer health and safety technologies has become more prevalent, but the number of errors that occur make those implementations unsafe. To raise awareness of these errors in Natural Language Processing (NLP), I propose the use of a Transformer Language Model (TLM) to create a chatbot that detects ambiguous textual inputs in these products. In addition, I propose the implementation of Part of Speech (POS) Tagging to aid ambiguity detection. I anticipate the outcome of this work will show that textual inputs in health and safety applications are more ambiguous than we are inclined to think.

1. INTRODUCTION

The progression of making Artificial Intelligence (AI) more human-like in terms of understanding and recreating human behavior has led to the increasing usage of technologies like AC and NLP. AC tracks things like eye movements, vocal inflections, and facial expressions, and analyzes the subtleties to determine what emotion a person is feeling. Although it has only recently been implemented into technology, AC is already being used for many purposes involving understanding of people's emotions. Some examples are of its use as a means to get feedback on advertisements and customer service support. AC utilizes NLP, a method that analyzes and replicates human language in particular by parsing written sentences [1].

Being able to detect human emotion and understanding the language has a huge array of applications, but there are a lot of imperfections that affect how useful this technology can be. For example, problems in facial recognition have been well established, like how subtle differences in facial expressions between different regions and cultures show that even basic emotions can be perceived differently [2]. In the same way, a written sentence can have different semantics based on the context and the presence of sarcasm or slang that NLP has yet to be able to distinguish perfectly. These inaccuracies that appear in NLP technology are far from being eliminated, yet the use of it is still being pushed in many applications.

Based on how common the issue of inaccurate interpretations of emotion and language understanding is, the conclusions that these technologies draw can be unreliable, considering how it is being applied in current technology, especially for the purposes of safety and mental well-being. In addition, the lack of regulation of these implementations allows for more mistakes to be released into products that people readily have access to. As more people become reliant on these technologies and the more they become integrated into normal lives, the more consequences there will be for errors that occur in AC and NLP techniques.

2. RELATED WORKS

The reasoning behind my proposal to create a tool that detects the ambiguity of textual inputs is built from recent studies that recognize the risks of AC errors in health and safety implementations. In the medical field, errors in textual-based NLP technologies can lead to incorrect diagnoses and medication errors. A study by Ford, et al. (2016) describes how errors in NLP algorithms used to extract medical concepts from clinical notes can lead to incorrect diagnoses and medication orders, which can be a severe risk to patients [3]. The research indicates that medical staff who use colloquial language in their notes may unintentionally introduce ambiguity into the text. As a result, NLP algorithms can misinterpret the meaning of the text, also leading to inaccurate diagnoses and inappropriate medication orders. This scenario can cause adverse drug reactions or other life-threatening consequences, which highlights the significant impact of textual ambiguity on patient safety.

Moreover, the study points out that clinical notes containing information on abnormal behavior are often phrased in ways that may not accurately convey the situation to an NLP algorithm. This issue may arise because the language used to describe abnormal behavior can vary widely and may not align with standard medical terminology. As a result, these notes present a significant challenge for NLP algorithms. This highlights the need for more advanced NLP techniques that can handle textual ambiguity to accurately extract relevant information from clinical notes.

There are also physical safety implications of errors in NLP. A study about Intelligent Transportation Systems highlights the importance of NLP in autonomous vehicle technology and its potential impact on safety (Zulkarnain, 2021) [4]. Autonomous vehicles rely heavily on NLP technologies to interpret and respond to driver commands, as well as to communicate information to passengers. However, errors in these technologies can lead to misinterpretations, which can increase the risk of accidents. For example, if errors in the NLP technology cause an autonomous vehicle to misunderstand a driver's command to slow down, it may not reduce its speed, potentially leading to a collision. Alternatively, if a vehicle's voice recognition system fails to accurately detect a driver's request to change lanes or exit a highway, it could cause unsafe driving behavior. The fact that the consequences of accidents involving autonomous vehicles can be severe, potentially resulting in injury or even loss of life, further displays the need for ambiguity of user input to be lessened.

3. PROPOSED DESIGN

As described below, the proposed chatbot will be designed with design specifications to detect ambiguous textual inputs using a TLM and Part of Speech (POS) tagging.

3.1 Dataset

The first step is to gather a variety of conversational texts, including examples of ambiguous sentences that could be challenging for the chatbot to understand. This data would mostly consist of samples of casual conversation from places like online discussion boards, social media, and transcripts of in-person conversation. Enough data should be collected to provide plenty of examples of ambiguity that would initially be difficult for an AI to understand. After the data is gathered from those multiple sources, it needs to be preprocessed by cleaning and properly formatting it. Then the preprocessed text needs to be tokenized into words or smaller phrases in order to be fed into the TLM for training. Tokenization allows the model to simplify the text to make it more efficient to process and treats each token as a separate entity to examine the language thoroughly [5].

3.2 Training with the Transformer Language Model

The next step would be to train a TLM that can be used by the chatbot to understand and respond to ambiguous textual inputs. This process entails feeding the preprocessed and tokenized data into a pre-trained transformer language model, such as GPT-3 or BERT, and using that to predict what the next word is when you give it an input of the preceding words in a sentence [6]. Depending on how accurate that is, the model's weights are altered to improve the accuracy of the guesses. Other possible steps to streamline the model would be to tune hyper-parameters to control the learning rate, batch size, and number of layers in the model, or to use the stochastic gradient descent algorithm for further optimization [7].

3.3 POS Tagging

Coupled with the use of transformer language models, POS Tagging is an essential component of making the chatbot able to discern the ambiguity of textual input. POS Tagging is a technique that labels each word as a corresponding part of speech based on its relationship with adjacent words in the text [8]. This helps the model to establish the context for the proper meaning of the word. POS Tagging should be implemented through hybrid modeling to get the benefits of different types of algorithms. The combination of neural network models and Hidden Markov Models (HMM) will contribute to a higher accuracy with POS tagging. The use of neural network-based models is beneficial because they can handle more complicated depictions of words and are better equipped for comprehending the right context behind meanings. Additionally, HMM is beneficial because it keeps track of sequential dependencies of words in a sentence as well as the probabilities of the possible parts of speech a word can contextually have [8]. By employing these models, the chatbot can use the entropy of the POS tag distribution to determine the ambiguity level of the inputted text.

3.4 Usage and Ambiguity Feedback

The chatbot itself will follow the basic conventions and qualities that a typical chatbot would have. The major external difference would be the ambiguity detector. The overall process would begin with the user typing a message into a text box, where the chatbot cleans and tokenizes the text. The input is encoded using a TLM and then put through POS tagging for each word. Based on the HMM's entropy of the predicted POS tag distribution, the chatbot can calculate how ambiguous the inputted text is on a scale of 1-10. The chatbot responds to the user with the predicted meaning of the user's input along with the ambiguity rating of the text. In the case that parts of the inputted sentence are ambiguous, the specific portion would be relayed back as such. The user can then modify their input as necessary and feed it back into the chatbot to reduce the ambiguity in the text.

4. ANTICIPATED RESULTS

In response to the problem of inaccuracies in NLP technologies because of ambiguous input, the implementation of the proposed chatbot will be beneficial to businesses, product testers, and general users of health and safety technologies. For businesses and product testers that develop products using NLP technology, having a way to see how easy it is for typical human input to be misinterpreted to cause errors in judgment will result in more quality testing and fine-tuning to make it more accurate. This will be an easy solution to counteract the lack of regulation of these newer technologies. In addition, by providing a more transparent and accountable approach to detecting and alerting to potential ambiguities, the chatbot will obtain more trust from the general public. Overall, it will raise awareness for users to show that our textual inputs are more ambiguous than we would normally assume.

5. CONCLUSION

The use of AC and NLP (NLP) technologies is becoming more prevalent, but with the increase in usage comes an increase in errors that make those implementations unreliable, especially in health and safety applications. I propose the use of a TLM chatbot that detects ambiguous textual inputs in these products, which could aid in reducing these errors. The proposed chatbot would use POS tagging to detect ambiguity in the textual inputs in health and safety apps, which has been shown to be significant in medical notes and autonomous vehicle technology. The significance of this project is highlighted by the potential implications of errors in health and safety implementations, which can lead to incorrect diagnoses, medication errors, and accidents. Therefore, ambiguity detection in textual inputs is essential to improve the accuracy of these technologies and ensure user safety.

6. FUTURE WORK

To expand on this proposal, additional features can make the project more accurate and give it a wider scope. One way to do this is by using more sophisticated techniques, such as deep learning, to allow the chatbot to learn from experience and make more accurate predictions. A broader step would be to test it with a healthcare system to see if ambiguity testing could be directly implemented into existing systems to prevent inaccuracies from occurring.

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