Sentiment Based Interaction in Robots

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Intelligent robots frequently need to understand requests from naive users through natural language. This interaction can be made more interesting for the user by providing the robot with the power of sentiment analysis and topic detection. The knowledge of both sentiment analysis and topic detection can increase the interaction level of the robot. The reply made by the robot should contain elements that can increase the interaction with the user. We propose an algorithm using sentiment analysis and topic detection. The algorithm tries to increase the social interaction of the robot.

Categories and Subject Descriptors: H.5.2 [**Sentiment Analysis**] Social Robots

Additional Key Words and Phrases: Sentiment Analysis, Topic Detection, Sociable Robots, Affect analysis

1. INTRODUCTION

Socially intelligent robots are not only interesting but also have a number of applications in our daily life. There are scientific and practical reasons for building robots that can interact with people in a human-centered manner [3]. There has been a vast research going on in this domain. Chatbots are based on simple pattern matching rules. We can avoid several issues concerning natural language processing and can quickly set up a dialogue scenario [4]. Social robots interaction with the human should be much more intuitive than just a simple dialogue. People should feel like talking with another person.

In order to make robots empathetic to the person they are talking, various studies have employed sentiment analysis in the dialogue. Sentiment analysis can be defined as a process that automates mining of attitudes, opinions, views and emotions from text, speech, tweets and database sources through Natural Language Processing (NLP) [6].

We are trying to propose an algorithm that will use sentiment analysis as well as topic detection. Based on the scores of both, it will try to figure out the best possible response. The response generated should be such that it should be in relevance to the topic that is being discussed. It should also add some new element to the conversation so that the conversation is extended. If we combine both sentiment analysis and topic detection, we think that the interaction could be far better than using each technique individually.

In section 3 we will present some of the previous work that has been done in this domain. In section 4 we will explain about Topic detection and some of the techniques that are used to accomplish topic detection. In section 5, we will explain about the Sentiment analysis and the techniques and resources that are used to accomplish that. In section 6, we will explain our proposed algorithm and how it can process sentiment as well as topic detection input. We will also provide some examples to show the utility of our algorithm. In section 7 and 8, we will provide conclusion and the possible future work.

2. RELATED WORK

Designing socially interactive robot is one of the interesting domain in which a lot of companies and universities are investing. We will explain few research projects and we will also highlight as to how our project is different from them.

(1) **TeenChat**: It is an adolescent-oriented intelligent chatting system which acts as a virtual friend. It can answer psychological domain-specific questions. It is an attempt made to show the application of social robots in the psychological field. It helps teens in coping stress by answering them according to the stress level that is judged by the robot.

(2) **PAL**: It collects numerous QA pairs from QA community into a local knowledge base, and selects a suitable answer to match the users question. It also accounts for personal information while answering the question.

    The drawback of both **TeenChat** and **PAL** is that most of the communication is needed to be in QA manner. In normal life, people do not talk in the form of questions and answers. People like to be more expressive. They would rather say things in normal sentences.

(3) **Microsoft Tay**: It is a chatterbot released by Microsoft on twitter. It fell victim to users tricks as they manipulated and persuaded her to respond back to questions with racial and offensive comments. This bot is not ideal for sociable scenarios where people are really sensitive to such things.

(4) **Cynthia Breazeal work**: She is the director of the Personal Robots Group (formerly the Robotic Life Group) at the MIT Media Laboratory. She is best known for her work in robotics where she is recognized as a pioneer of social robotics and human-robot interaction.

    Kismet
    Kismet is said to be one of the earliest social robot[10]. Kismet does not speak any language but reacts in a way that is similar to how human react using social cues.

    Leonardo
    Leonardo is a good example of a social robot. Most of the work has been done on the psychology of understanding as to how the mind works[11]. It is claimed to be the most expressive robot. Leonardo does express things using hand gestures, eye movement, and other body gestures.

    It is different to what we are proposing as we are giving the robot the power for Natural Language Generation. Our proposed algorithm can help the robot in making the interaction much longer by generating the correct and relevant replies. Our system also records the user preferences according to the different behavior in different situations. It generates replies in such a way that they are more relevant to the context.

    We also acknowledge that the level with which Leonardo responds using the hand gestures and other social cues is truly remarkable. We think this power of social cue could really make our system more impressive.

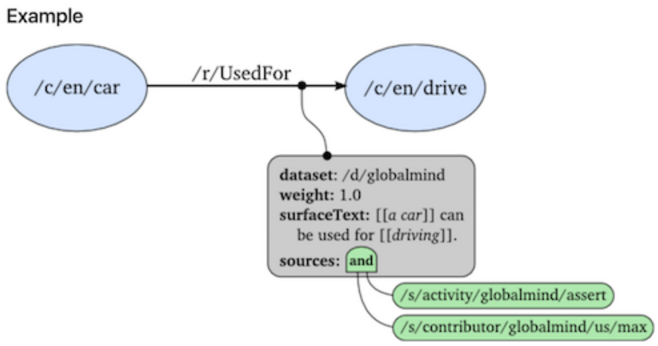

Fig. 1. An example to show a relationship in nodes present in ConceptNet

3. TOPIC DETECTION

Topic detection algorithms categorize documents, sections of documents, news stories, or conversational utterances using natural language processing and often machine learning techniques [6]. There are various kinds of techniques that are employed in order to perform topic detection. Some of them are:

Corpus based approach: These techniques use the power of already annotated corpus or dictionary and then try to categorize the sentence or a document accordingly.

Clustering Keyword approach: These approaches treat the problem of identifying and characterizing a topic as an integral part of the task.[12]. Firstly, a list of the most informative keywords is extracted. Subsequently, a cluster of keywords is identified and their center is defined, which is taken as the representation of a topic.

Semantic based approach: Semantic based approaches are used to focus on underlying semantic structures of the data and go beyond linguistic restrictions to identify topics embedded in the user's conversations[13].

In our proposed algorithm we are using a corpus based approach. We are proposing to use conceptNet5 or/and TDT2 as the corpus in our approach. TDT2 data is provided by LDC (Linguistic Data Consortium). TDT2 data contains news data collected daily from nine news channels. The TDT2 corpus support 3 tasks:

(1) finding topically homogeneous sections (segmentation).
(2) detecting the occurrence of new events (detection).
(3) tracking the re-occurrence of old or new events (tracking).

ConceptNet is a multilingual knowledge base, representing words and phrases that people use and the common-sense relationships between them. The knowledge is stored in the form of a graph database. The nodes of the graph are concepts in the form of normalized words and phrases, and the relationships between the concepts are the edges. There are around 24 types of relationship that can be defined for a node in the database. Figure 1 shows the relationship between 2 nodes.

ID	PosScore	NegScore	Terms	Gloss
1740	0.125	0	Able#1	Having the necessary skill

Fig. 2. A sample tuple in SentiWordNet

Category	Example Term
emotion	anger
cognitive state	doubt
trait	competitive
behaviour	cry
attitude	skepticism
feeling	pleasure

Fig. 3. A sample categorization of words in WordNet-Affect

4. SENTIMENT ANALYSIS

Sentiment analysis can be defined as a process that automates mining of attitudes, opinions, views and emotions from text, speech and database sources through Natural Language Processing (NLP). Sentiment analysis involves classifying opinions in text into categories like ”positive”, ”negative” or ”neutral”. It’s also referred as subjectivity analysis, opinion mining, and appraisal extraction[6]. Techniques that are majorly used in Sentiment Analysis are:

Lexicon based approaches : These approaches use the vocabulary content to determine the opinion present in a text. These approaches compare the content of a test document with their labeled dictionary.

Machine Learning approaches : These approaches build classifiers using the corpora of labeled documents. These classifiers try to find the best text feature to use for their particular domain.

Conceptual approaches : These methods use Web ontologies or semantic networks to accomplish semantic text analysis [1]. This helps the system grasp the conceptual information associated with natural language opinions. The Concept based approach rely on the depth of the knowledge bases it uses.

In our project,we are using a lexicon based approach. We used SentiWordNet, an opinion-mining resource. This is based on the WordNet. This resource maps WordNet synset to sentiment scores. Figure 2 shows the example of a sample tuple in SentiWordNet. The problem which we want to address in our project is about generating replies which can make the user believe as if he/she is talking to a real person and not a robot. The information that is provided by SentiWordNet is not enough in order to provide the best solution.

We introduced another resource called WordNet-Affect in our project in order to better analyze the sentiment of the user. Figure 4 shows a sample categorization of words. It helps in narrowing down a particular emotional state.

5. PROPOSED ALGORITHM

In our proposed algorithm, we use both sentiment analysis as well as topic detection.

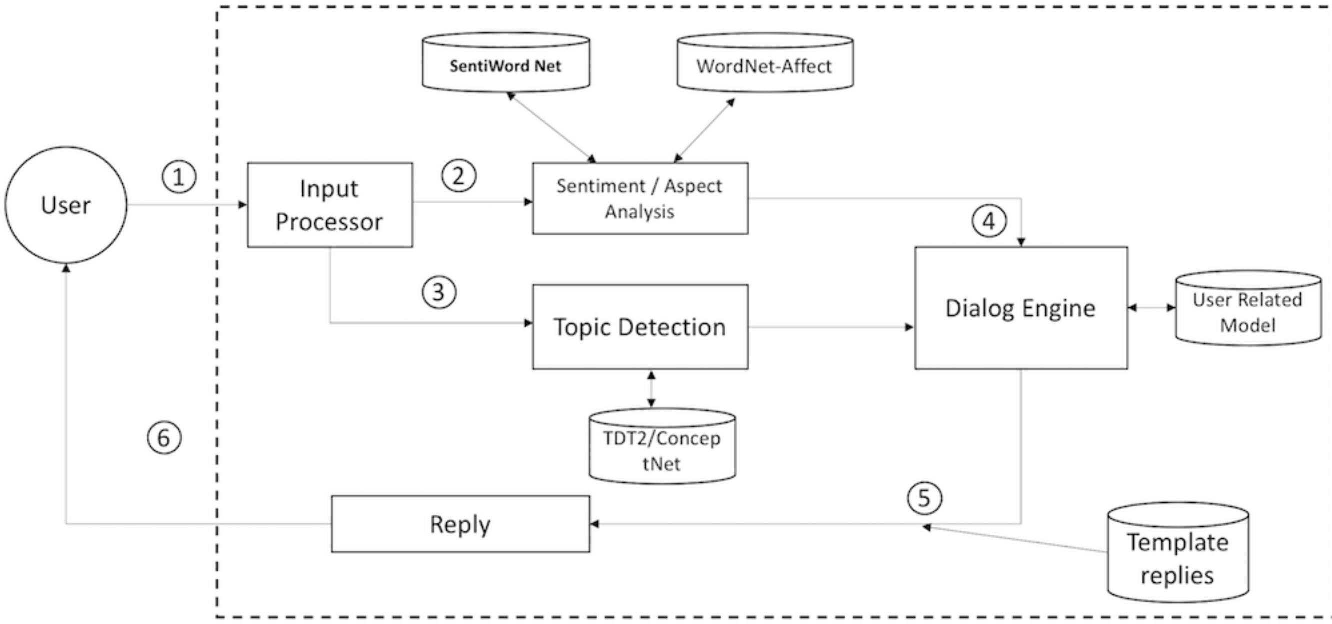

Fig. 4. The flow diagram for the proposed algorithm

Figure 4 shows the flow diagram of our algorithm. The area in the dotted line represents the part of the algorithm that is implemented inside an interface to which the user will interact. The interface could be a robot or it might be the case that the user interacts with an avatar on the mobile application.

Input Processor: This module analyzes each input of the user, tries to segment it if necessary (i.e. when there is more than one sentence), categorize it, extract the important elements and generates some type of semantic representation of the input. Our algorithm can work on both kind of input, text as well as voice inputs. In the case of voice input, our input processor module will have a speech to text converter. Although, getting an emotional state from voice is out of the scope of our current project but it can also be a parameter to get the users excitation level.

Sentiment/Aspect Analysis: This module performs the analysis by taking the input from Input Processor. It tries to judge a sentiment level for the sentence depending on the keywords present in the sentence. It also defines the category of specific emotion. Getting the correct category will help in generating a fitting reply which will engage the user.

Topic Detection: It uses a large corpus/dictionary such as the one provided by LDC in order to identify the topic of the input. Categorizing the input helps in limiting the scope of the reply. It gives a locality of reference and helps to restrict the knowledge domain required for the current conversation.

Dialog Engine: This module tries to maintain a balance by taking input from both Topic Detection module and Sentiment analysis module. It deduces the apt reply using both the input from Sentiment/Affect analysis module and the topic detection module. It also uses the data store which has the information regarding the user.

Dialog Engine is also responsible for Natural Language Generation, for maintaining the dialog state and how the rules are computed based on the weights. It maintains the dialog state and the turn of the dialog.

Template Replies: These are the templates which are added to the replies in order to make them identical to how a human will answer. We add our own feelings while replying to simple things.
i.e. Let us take an example:

User: ”I got full marks in the test.”

The robot might reply “you did a great job.” But the template addition will convert this sentence into

Robot : “I am really happy that you did a great job.”

User Related Model: Robot can save specific profiles of the user as to if he is sad, he likes to listen some particular kind of songs. It can save the rules as the situations come along and can use these rules later on in normal interactions. These rules will give more insight into user habits. It will give the power to the robot to do implicit actions when a specific event occurs.
It is necessary to learn after interacting with humans as that is a thing which connects us. We remember things that we discuss with each other and all the next interactions are built on the previous interactions.

Example:
if a user is happy he listens to music.
If a user is hungry he wants a sandwich.
The user wants coffee in the morning.
These are different events for the robot.let us say that from a dialogue with a user if it can be inferred that user is happy then the robot can ask the user if it should start the music. Similarly, others will work.

6. PROPOSED ALGORITHM ANALYSIS AND EXAMPLES

In this section we will explain the basic flow of our algorithm by the use of an example and at the same time we will also try to see if our algorithm can perform better if put in a scenario where [3] is performed.

There could be various scenarios in which the user may want to talk about his feelings towards a particular topic. Let us take an example where user is upset about the loss of his favorite player Roger Federer in Tennis.

User : “I am so sad that Roger Federer lost the match.”

We are assuming it to be a text input. In case, the input is of another form we will take the steps according to the way explained in the description of Input Processor.

Step 1: Input Processor will take the input and will segment it to find the main keywords and part of speech in the sentence. After figuring and tagging the modified text will be forwarded to both the modules for sentiment analysis and topic detection.

Step 2: Sentiment analysis module will categorize it under negative feeling because of the presence of the word "sad" and "lost". Aspect analysis will put this under the category of sorrow.

Step 3: Topic Detection will use the TDT data provided by LDC and will figure out that Roger Federer is related to Tennis. Tennis is a sport. It depends on our algorithm as to what amount of detail we want to extract as TDT data will also have that Roger Federer has won a lot of titles and as to what has been said about him in news. All this information will go to Dialog engine.

Step 4: Dialog engine will get the input from both the modules and will process that the user is feeling sad because Roger who is a tennis player has lost.

The robot has to generate a text such that it should be able to have a feeling of compassion. Our dialog engine has programmed rules as to how to react when the people are sad or happy. This programming is very general purpose as to when a user is sad, the robot should try to use words which are compassionate and when a user is angry then words should be chosen, which can have a calming effect. Now our dialog engine can make a reply such as:

Robot: "It is just a game. We all know that Roger is the best"

The dialog engine also has the access to the user model. Dialog engine will check if there is rule defined for a sad situation. In case there is a history that last time user had tea when he was sad then the reply would change to something like:

Robot: "It is just a game. We all know that Roger is the best. How can I help you ? Would you like to have tea?"

In case, there is no rule defined then the robot can try to get a rule and the reply would be:

Robot: "It is just a game. We all know that Roger is the best. How can I help you ?"

Step 5: Template reply based on the sad situation will be:

Robot: "I am really sorry but it is just a game. We all know that Roger is the best. How can I help you? Would you like to have tea?"

6.1 Comparison with T. Jesse et al

Jesse et al in [3] presents a dialog agent for mobile robots which communicates with users through natural language. Robots learn semantic meanings from the conversations with. We will try to project a scenario in which we will try to implement our algorithm in the same scenario that they presented.
In [3] the robot takes order from screen input and tries to clarify the confusions using a dialog manager. In the case of our algorithm, the robot not only will save only orders but it will also be able to perform various sentiment analysis. If a user writes down that

User: "I am sad and I want you to play music for me."

Now the robot can make a rule that when the user is sad he likes to listen to music.
We saw that in [3], the robot learns different synonyms from the user by using a dialog manager which

could be really annoying. We are using a corpus of words and synonyms to build this dictionary.So, Our robot will never ask these questions because it has the access to all synonyms.

Although, the approach presented in [3] is good in the case when you are making a robot which should perform a specific field job. In that case, it does not have to load a heavy dictionary. This will be effective because most of the words might not be used. But we think that the time that can take a robot to become truly helpful in any scenario will be too much. It will be something like teaching a kid what mean what. But in our approach, the robot does not need to learn basic things and the new rules generated are also added which makes it more efficient.

7. CONCLUSION

We tried to prove that imparting the knowledge of sentiment analysis and topic detection can increase the robot understanding. We gave an insight as to how the proposed algorithm will work in various scenarios. We showed how the algorithm makes the robot more interactive. We also demonstrated some insight as to how the robot generates replies so that the user should feel more connected.

8. FUTURE WORK

The future work which we think will be apt for our project is gesture implementation. Humans use a lot of gestures and social cues while speaking. We think that implementing gestures such as the motion of hands, gaze etc.. can make the robot more social. The work done by Cynthia Breazeal could be a great motivation for future work for our project.

We also think that giving the robot some distinctive behavior such as giving them psyche of a child or a person in the age of 60-70 year could be interesting. The robot can be grandmother robot for kids which tells them stories and rhymes. Giving psyche of a child can help some kids which find it really difficult to get social in childhood. This robot can be their companion.

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