Conditional Entropy Based Retrieval Model in Patient-Carer Conversational Cases

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***Abstract*—Assistant Robots can be an efficient and low-cost solution to Patient Care. One important aspect of Assistant Bots is successful Communication and Socialization with the Patient. A new Conditional Entropy Retrieval Based model is proposed and also an Attitude Modeling based on Popitz Powers. The Conditional Entropy Model and the Attitude Model are combined in order to identify Attitude Changes in Dialogue Interactions between Patients and Doctors.**

***Keywords*-Word Vector Representation, Dialogue, Entropy, Retrieval -Based Model, Robot, Assistant Bot, Chatbot, Popitz Powers**

I. Introduction

A. Patient-Robotic Assistant Dialogue Interaction

During the last years, many systems were designed that aim to facilitate the verbal communication between humans and Robotic Assistants and specifically Healthcare Assistants.

Automatic speech recognition aims at a natural interaction between humans and robots. Human speech can be noisy and not straightforward in terms of the context and any system that interpretes or produces human-robot dialogues must be able to perform efficiently. For example, in [25], in the Spoken Dialog Management System Design which is a Partially Observable Markov Decision Process, POMDP, proposed by Pineau and Thrun in [7] is used. The HPOMDP framework provides the mechanism for modelling uncertainty about what the user is trying to communicate [8].

B. Dialogue Retrieval Based Models

Natural language processing is a field of computer science, artificial intelligence, and computational linguistics concerned with the interactions between computers and human, natural, languages. As such, NLP is related to the area of human-computer interaction. Up to the 1980s, most NLP systems were based on complex sets of hand-written rules. Starting in the late 1980s, however, there was a revolution in NLP with the introduction of machine learning algorithms for language processing. This was due to both the steady increase in computational power and the gradual lessening of the dominance of Chomskyan theories of linguistics leading to a machine-learning approach to language processing[22]. Some of the earliest-used machine learning algorithms, such as decision trees, produced systems of hard if-then rules similar to existing hand-written rules. However, part-of-speech tagging introduced the use of hidden Markov models to NLP[21], and increasingly, research has focused on statistical models, which make soft, probabilistic decisions based on attaching real-valued weights to the features making up the input data. Such models are generally more robust when given unfamiliar input, especially input that contains errors. Finally, the latest trend applies Deep Learning on Natural Language Processing, with DeepMind one of the most widely known[23], currently belonging to Google. Recent research has increasingly focused on unsupervised and semi-supervised learning algorithms using a combination of annotated and non-annotated data. We will propose an innovating approach based on Information Theory for Natural Language Processing [10], [11].

C. Socially Intelligent Robotics

In the research area of Assistant Bots for healthcare services, social skills are necessary for robots in order to be acceptable by the users [4],[5]. Consequently, the Patient-Assistant Relationship in terms of effective communication and emotional intelligence on the robot's part has been given emphasis. This new approach is called Social Assistive Robotics, SAR, [19]. SAR represents the merging of two traditional robotic applications: assistive and interactive robotics and the aim is to integrate social skills in the work of robotic patient-caregivers. This area has been very active with robotic research, such as Brian in 2008, Clara in 2005 and SIRA in 2005 in [4], [1], [24], [25].

Our work is organised as follows: first we introduce a novel Conditional Entropy based Retrieval Based Model that is destined for choosing the suitable response phrase from a database of response phrases, secondly, a new model of

Attitude Space and Attitude Change that are based on Heinrich Popitz's Powers is presented and finally, in the last part, we analyse and provide the results from our experiments on hypothetical conversational scenarios between patients and carers.

II. Conditional Entropy Retrieval Based Model in Dialogue Systems

The goal of a Bot Assistant is to be effective in Patient-Assistant communication. In the case of verbal communication, both the perception of the information and the level of friendliness are important for the Robot to accomplish its task in communicating with a patient.

Information Theory and more specifically Entropy have been applied before as we mentioned, [10]. Many problems in natural language processing can be reformulated as classification problems in which the task is to estimate the probability of class a occurring with context b or p(a,b) using the criterion of Entropy Optimization. Since we are dealing with Assistant Robots, within the scope of which are certain phrases and certain tasks, and since, in the communication with a Robot, we are looking for a suitable reply phrase B of the Robot when phrase A coming from the patient is given, we used the Criterion of the Minimization of the Joint Normalized Conditional Entropy $H(B/A)$.

Let us assume that the patient communicates a sentence A to the robot which consists of some words. The Robot, based on that given sentence A, has to respond with a proper sentence B that makes sense as a proper reply to A. Let us also assume that there are dialogues between Robot and patient for every case stored in memory. How can the Robot choose fast the most suitable answer sentence B from the dialogues without the use of large Markov matrices that need to be stored in memory?

The representation of sentences was either a zero-one vector, according to which words appeared in each sentence, or a probablistic vector representation based on word occurrencies. In order to highlight the connections between the words in the dialogues that belong to the same sentence as well as the connections between the words that belong to sentence A and the suitable response B, we chose a different representation of each sentence vector. If we want to use the Minimization of the Conditional Entropy, $H(B/A)$, as a criterion, we should couple th respective words beforehand. For this reason, we form an Adjacency Matrix ADJ that has the number 0 when there are no connections and the number 1 in position ADJ(i,j) if word i is in the same sentence as word j or if word i is in sentence A and word j in sentence B of the corresponding reply(Figure 1). So, now, our Word Represntation Vectors are the rows of the Adjacency Matrix ADJ. In this way, the necessary couplings of words have been created beforehand, based on our texts so it is expected when the user inputs sentence A, the Robot will estimate the Conditional Entropy $H(C/A)$ for all sentences C in our database and will return the sentence C that minimizes the Normalised Conditional Entropy $H(C/A)$.

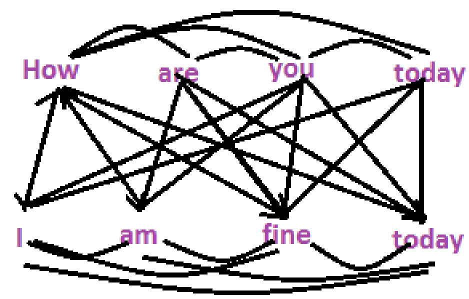

Figure 1. The Representation Vectors w_i for the Words come from the rows Adjacency Matrix ADJ where there are zeros everywhere except when two words can be found in the same sentence or two words can be found in a sentence and the corresponding dialogue answer to that sentence.

At this point, we have to note that since every word is represented as the respective row of the Adjacency Matrix ADJ, the Entropies of sentences A and C are given by the following formulas that apply to Joint Entropies. If sentence A consists of words w_{33}, w_2 and sentence C consists of the words w_5, w_{10}, w_{25} then

$$H(C/A) = H(w_5, w_{10}, w_{25}/w_{33}, w_2) =$$
$$-\sum(p(w_5, w_{10}, w_{25}, w_{33}, w_2) \cdot logp(w_5, w_{10}, w_{25}, w_{33}, w_2))$$
$$+\sum p(w_{33}, w_2) \cdot logp(w_{33}, w_2))$$

III. Attitude Modelling in Patient-Robot Dialogue with the help of Popitz Powers

Heinrich Popitz believes that Power is present in all Human Social Relationships. treats power as an essential concept of the social sciences. We suggest the integration of Popitz Powers in the Dialogue Communication between the Patient and the Bot Assistant. When a Patient and a Care engage in socializing through dialogue, they still exercise power on one another.

The Popitz Powers that are applicable to Dialogue Patient-Robotic Assistant Interaction are Trust, Love and Action. Trust is implemented when the communication establishes a relationship between the two parties that is based on Trust and the clear, explicit and accurate expression of events. Love is implemented if the communication involves any kind of sentiment or appeal to sentiment. This could vary from a mere expression of a feeling to trying to manipulate the other party through invoking certain emotions. Last but not least, Action is implemented in the communication where there is a clear warning for taking more drastic measures and an urge to instant action.

In terms of Attitude, these Powers can be translated into the words Trust, Sentiment and Instrumental Power. We call the last Power Instrumental because the Assistant Robot and the Patient will possibly engage in this kind of interaction in case the patient displays warning signs of neglecting themselves or self-destructing tendencies and the Assistant will have to warn them about this behavior and possibly to reach out to the Instruments that are responsible for their health such as the doctor or a psychiatrist. Attitude can be thought of as a Vector Space with three dimensions, Trust, Sentiment and Instrumental Power. Throughout a dialogue, there are utterances and interactions of clear Trust, clear Sentiment and clear Instrumental Power as well as combinations of them(Figure 2).

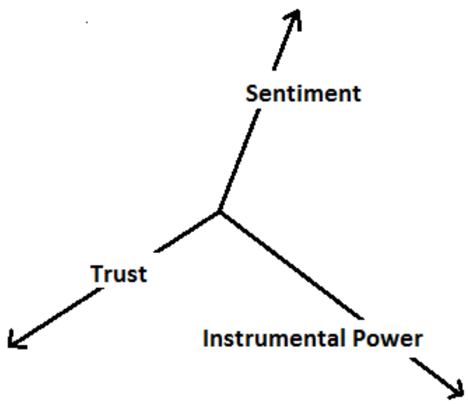

Figure 2. Trust, Sentiment and Instrumental Power Vector Space Model.

Trust, Sentiment and Instrumental Power can model Attitude Change as the Conditional Entropy in interacting dialogue phrases of different Attitude. Dialogues, as we mentioned in the previous section can be modeled as networks of interactive words in a context of respecting Attidute interactions. Practically, this means that if Agent K is having a conversation with Agent J then we will form three Word subnetworks. The first Word Subnetwork will contain linked words from the interaction during which K addresses a sentence to J in a Trust Attitude and J also responds with Trust. The second Word Subnetwork will connect words in sentences where K addresses a sentence using the Sentiment Power and J responds using the same Attitude, Sentiment. The same goes for interactions of the type Instrumental Power-Instrumental Power.

When those networks are formed, each conversation that holds those word connections, addresses a phrase and the other party responds with the same attitude. So, we consider that there is minimum information load in terms of Attitude throughout every single of those three dialogues as no change in Attitude takes place. In a real conversation though, things are not as flat. When we talk to each other, one does not respond to the other in the same way, we do not have interactive couples of phrases of the same Attitude. In real life dialogues, when a person addresses us a question in a certain Attitude, our response Attitude may vary from Trust to Sentiment or to Instrumental Power. The Attitude Change has also been studied by [20]. This Change in Attitude can take place due to our feelings, a spur of the moment or due to an intention we have to stirr the conversation and the events to a specific direction. In this work, after forming the basic Attitude subetworks dialogues, Trust-Trust, Sentiment-Sentiment, Instrumental Power-Instrumental Power, we study the Conditional Information throughout Attitude Changes among these subnetworks.

IV. Patient-Assistant Healthcare Dialogues

The data we used for the second experiment were three dialogues in the three different attitudes, Trust, Sentiment and Instrumental Power. The dialogues were based on a sensor results report by the *Clinical Skills Laboratory of Medical School of Aristotle University of Thessaloniki.* and also based on the respective recommendations for each medical symptom that was recorded by the sensors. More specifically, the symptoms that were recorded and reported by the sensors regarding depression and were:

- Insomnia
- Crying
- Hypertension
- Reduced Mobility
- Reduced Social Interaction
- Agitation
- Depressive Mood

The dialogues that were produced comprised of couples of patient-assistant interactions in the form:

Assistant: I noticed you have insomnia.
Is there a reason why you can't sleep?
Patient: I was nervous.
Assistant: You can take deep breaths.
You can drink a glass of milk or pour yourself a Louiza tea.

As we can see, in the first Assistant-Patient interaction, the Assistant reports the symptom that was recorded by the sensors and asks the patient about it and the patient complains about this symptom by replying to the assistant. In the second Assistant-Patient interaction, the Assistant, based on the previous two phrases, which are the symptom related question and the patient's complaint, provides a suitable recommendation. The content of the recommendations as well as the complaints is edited by psychologists and converted into basic dialogues.

After the basic phrases are created for each role in the patient-assistant interaction, three different attitude variations were produced of the initial interactions. In the first variation, the assistant enquires and recommends in an attitude that provokes Trust as well as the patients expresses his/her complaint in a way that is clear and neutral and responding to that Trust level towards the Assistant. In the second variation, the patient complains in an intense and sentimental way and the assistant also conveys its recommendation in a Sentimental way. Finally, in the last variation, the patient complains in a way that might defy his/her doctor's instructions and medication and might even display self-distructive tendencies. This is the case when the recommendation of the assistant is realised in a way that makes a direct reference to the instrumental power that may be further used in order to make the patient as soon as possible realise the potential dangers and to comply with the doctor's suggestions.

After the three attitude variations were produced, our network of inter-connected words is formed. All the words that are present in the three texts are recorded. The duplicates are deleted. For each one of the three attitudes, Trust, Sentiment and Instrumental Power, the words that happen to be in the same sentence as well as the interaction sentence, symptom+complaint - recommendation, are connected symmetrically in the adjacency matrix. In this way, some information on the context of words is stored, with respect to same-sentence words. Moreover, the interacting words of each pair, symptom+complaint - recommendation, link the words semantically and store information in the Adjacency matrix with respect to the sentence's content.

As a first step, we remove punctuation and we create an Adjacency Matrix where we connect the words that are found in the same sentence as well as the words that belong to a dialogue interaction couple of sentences.

In the next step, we feed each of the Dialogue Phrases to the input and record the most suitable response sentence that each algorithm gives us. The three Retrieval Based Algorithms that are used are our Conditional Entropy Model, Deep Neural Networks and RBF Kernel Support Vector Machines. The success rate is recorded in the Tables I,II and III. Support Vector Machines displays a better fit for the presence of some words in the response sentences but not for a large enough percentage of them and Deep Neural Networks returned incorrect words and most of them were common as they are very successful in Recognition tasks but the disadvantage is that they require large datasets to train on and our dialogues are small and 3 in number. Our method seems to outperform the other two in this experiment.

A. Attitude Change Conditional Entropy Flows

For this experiment, the Dialogues of two Doctor-Patient Interaction videos were transcribed. The videos are courtesy of the *Clinical Skills Laboratory of Medical School of Aristotle University of Thessaloniki.* and their aim to was to videotape one Medical Examination where the Doctor

Table I
RETRIEVAL SUCCESS RATES IN CONDITIONAL ENTROPY RETRIEVAL BASED MODEL, DEEP NEURAL NETRWORKS AND RBF KERNEL SVM FOR TRUST TEXT

Method	Success Rate %
Conditional Entropy	87.5
Deep NN	85
RBF Kernel SVM	52.3

Table II
RETRIEVAL SUCCESS RATES IN CONDITIONAL ENTROPY RETRIEVAL BASED MODEL, DEEP NEURAL NETRWORKS AND RBF KERNEL SVM FOR SENTIMENT TEXT

Method	Success Rate %
Conditional Entropy	93.54839
Deep NN	90
RBF Kernel SVM	53.1

Table III
RETRIEVAL SUCCESS RATES IN CONDITIONAL ENTROPY RETRIEVAL BASED MODEL, DEEP NEURAL NETRWORKS AND RBF KERNEL SVM FOR INSTRUMENTAL POWER TEXT

Method	Success Rate %
Conditional Entropy	96.77419
Deep NN	82.2
RBF Kernel SVM	54.41

displays a proper behaviour or is a "Good Doctor" and one Medical Examination where the Doctor displays an improper behaviour that should be avoided or is a "Bad Doctor". We recorded the two conversations in text files. Subsequently, we created the three Attitude variations, Trust, Sentiment and Instruemntal Power, for the interacting phrases of the two Dialogues and we connected the words in those three subnetworks. Because of these connections, we expect the Conditional Entropy-Uncertainty to rise everytime an Attitude Change taks place in the real dialogues. Therefore, we computed our Conditional Entropy metric in every successive couple of phrases in the "Good Doctor" and the "Bad Doctor" dialogues.

In Figure 3, we present some of the phrases where the Conditional Entropy displayed an increase so we expect a Change in Attitude and the respective phrases.

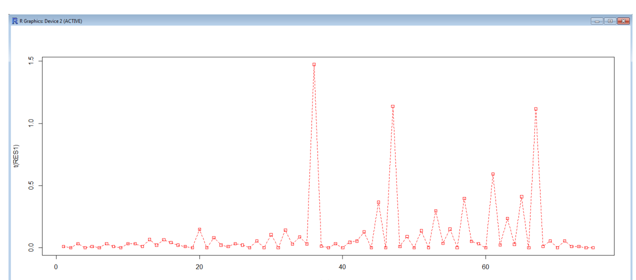

Figure 3. Good Doctor Dialogue Conditional Entropy Flow

In Figure 4, we present some of the phrases where the Conditional Entropy displayed an increase so we expect a

Change in Attitude and the respective phrases.

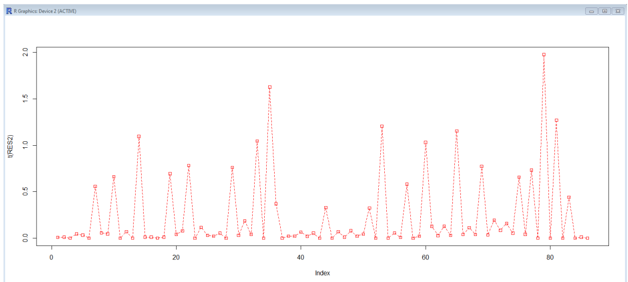

Figure 4. Bad Doctor Dialogue Conditional Entropy Flow

V. Conclusion

We showcased that for the Assistant Chatbot-Patients communication, there is an Entropy based Response Retrieval model that can be used that requires only a compact Adjacency Matrix based on the dialogues in our disposition. This Adjcency Matrix links the words of the same sentence as well as the words of different sentences that correspond to question-answer pairs. The results show that even in small training datasets, this method outperforms up to date methods for automated communication. Finally, we used this Conditional Entropy algorithm to model Attitude changes in dialogue interactons in healthcare.

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VI. Appendix

A. Trust-Trust Dialogues between Patient and Bot Assistant based on the Sensor Measurements

I noticed you have insomnia. Did you experience difficulty sleeping? Is there a particular reason?
I was nervous. You can take deep breaths. You can drink a glass of milk or pour yourself a Louiza tea. You can read a book. You can take a warm bath.

I noticed you have insomnia. Is there a reason why you didn't sleep well?
I think I have been eating a lot at night.
Don't eat coffee, alcohol or eat too much 3 hours before you go to sleep.

I noticed you have insomnia. What did you do wrong and you can't sleep well?
I drink too much water and I need to pee many times at night.
Don't drink too much water before you go to sleep.

I noticed you have insomnia. Is there a reason why you didn't sleep well?
I do my exercise routines in the evening and then I cannot sleep.
Try to exercise earlier in the evening in order to relax later.
I noticed you have insomnia. Is there a reason why you didn't sleep well?
I remembered those things again and I got a little sad.
Try to avoid discussing unpleasant subjects before going to sleep.
I noticed you have insomnia. Is there a reason why you didn't sleep well?
My friends came and my routine got disrupted.
Keep a steady routine before going to bed.
I noticed you have insomnia. Is there a reason why you didn't sleep well?
TV is always showing bad news.
Try to avoid unpleasant TV programs before going to bed.

I noticed you have insomnia. Is there a reason why you can't sleep?
I feel extreme heat.
You can lower the room temperature. You can wear light clothes. You can drink a cool glass of milk or water. You can take a shower with lukewarm water.

I noticed you have insomnia. Is there a reason why you can't sleep?
I feel pain.
You can change your sleeping position into one that is more comfortable. You can take a painkiller.

I noticed you have insomnia. Have you started a new drug recently?
I have started this new pill recently.
You can discuss with your doctor about possible medication side-effects.

Have you been crying?
I feel sad.
Talk to someone you love and cares about you. You can go out for a walk. You can read a book. You can watch TV.

Have you been crying?
Something happened to a person I care about.
Talk to someone you love and cares about you. You can call them tomorrow.

Have you been crying?
I feel sad.
Have you started a new drug recently?

Have you been crying?
I feel guilty. It's my fault.
Don't blame yourself. Talk to someone you love and cares about you. You can talk to a psychiatrist.

Have you been crying?
I am moved by the movie. It was so sad.
Talk to someone you love and cares about you.

Have you been crying?
I don't feel good about myself.
Talk to someone you love and cares about you. Talk to a psychiatrist.

Have you been crying?
I feel sad. I feel bad. I don't know why.
You can write down your thoughts in order to realize your negative feelings. You can talk to someone who cares about you.

You haven't been moving your body a lot recently. Is there something wrong?
I feel pain.
Try small exercises. Avoid movements that hurt. You can take painkillers. You can have a massage.

You haven't been moving your body a lot recently. Is there something wrong?
I feel dizziness.
Avoid sudden movements. Measure you blood pressure. Have you skipped any meals?

You haven't been moving your body a lot recently. Is there something wrong?
I feel tired.
Listen to your favorite music. Eat a small chocolate. Take a small walk. Take a warm bath.

You haven't been moving your body a lot recently. Is there something wrong?
I am not in a good mood.
Listen to your favorite music. Eat a small chocolate. Take a small walk. Call your friends.

You haven't been moving your body a lot recently. Is there something wrong?
I didn't sleep well last night.
Listen to your favorite music. Watch TV. Take a small walk. Call your friends.

You haven't been moving your body a lot recently. Is there something wrong?
I am bored.
Maybe you can start a new hobby. You can call someone you care about. You can watch TV. You can go for a walk. You can eat a small chocolate.

I noticed you haven't met with someone or even talked to someone these last days.
I am not in a good mood.
You can start a new hobby. You can go to church. You can call a friend or family member.

I noticed you haven't met with someone or even talked to someone these last days.
I don't have friends.
You can organize your schedule from the previous day. You can take your friends with you when you go out.

I noticed you haven't met with someone or even talked to someone these last days.
I don't have time.
You can choose free activities and share them with your friends. You can visit a friend. You can call a friend over. You can call a friend.

I noticed you haven't met with someone or even talked to someone these last days.
I save money.
You can sit on the balcony for a while. You can call a friend. You can go for a short walk.

I noticed your blood pressure is increased lately. Are you felling ok?
I fell sad. I feel nervous.
Avoid coffee and alcohol. Call a friend or family member. You can go out for a walk.

I noticed your blood pressure is increased lately. Are you felling ok?
I feel pain. I'm in pain.
You can lie down. You can eat more fruit and vegetables. You can call your doctor.

I noticed your blood pressure is increased lately. Are you felling ok?
I didn't take my pills.
Take your pills as soon as you remember it. If next dose is close, just wait for next dose. Talk to your doctor.

I noticed your blood pressure is increased lately. Are you felling ok?
I had a bad night sleep.
You can talk to your doctor. Avoid coffee, alcohol and smoking.

I noticed your blood pressure is increased lately. Are you felling ok?

I had my drugs changed recently.

Talk to your doctor for possible side-effects. Avoid coffee, alcohol and smoking.