



Conditional Entropy Retrieval Based Model in Patient-Carer Scenarios and Attitude Change: Potential Uses with Affective Assistant Chatbots

Meropi Pavlidou

Supervisor: Assoc. Prof. Panagiotis Bamidis

Co-supervisor: Dr. Charalambos Bratsas

Co-supervisor: Dr. Nikolaos Hasanagas

February 10, 2017

¹Special Thanks to: Prof. Ioannis Antoniou and Dr. Antonis Billis



Abstract

Assistant Robots can be an efficient and low-cost solution to Patient-Care. One important aspect of Assistant Bots is succesful as well as Socially Intelligent Communication 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 record Attitude Changes in Dialogue Interactions between Patients and Doctors.



keywords: Retrieval-Based Model, Conditional Entropy, Assistant Chatbot, Attitude Change, Popitz Powers

Chapter 1

Introduction

1.1 Healthcare Robotic Assistants



Figure 1.1: Artificial Intelligence by **bykst** on Pixabay

Ageing population is a phenomenon that occurs when the median age of a country or region increases due to rising life expectancy and/or declining fertility rates. As stated in [1], this is a phenomenon for the modern world. By 2050, people over the age 85 will increase by 300 % compared to the year 2015. Aging population already strains the current health service system. There are shortages in the workforce of health sector and there is a need for space expansion of care facilities. When people are old, there is a reduction in physical activities which results in a reduction of their independence and, subsequently, their prolonged stay in hospital facilities where they need attendance or their nursing at home. While these aged people may be in need of 24-hour surveillance, usually due to behavioral, social and economic factors this is not possible. Because of these issues, home-based and community-based healthcare services have started to assist elderly people in the developed world in order to:

- Relieve the pressure of health services while keeping up with the high demand in the quality of the services delivered
- Helping the elderly people to be close to their families achieving a certain level of independence.
- Help the nursing staff in their every-day repeating duties of taking care of the patients accurately and leaving their fatigue aside.
- Provide higher efficiency and quality of services through robots in the area of teleoperation and rehabilitation processes.
- Support the elderly patients not only physiologically but also psychologically or in terms of memory assistance such as personal robots, companion robots and entertainment robots.
- Participate in therapies of cognitive disabilities such as autism spectrum disorder.



Figure 1.2: Enon Assistant Robot

Due to the above need for assistance of people in health-care facilities or in home-based nursing combined with the ongoing Technological advances in Assistant Robots, the interest in and research on personal robots has been rising rapidly.

1.2 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.



In the research area of Assistant bots for healthcare services, social skills are necessary for robots if we want them to be accepted by the users [3],[7]. Consequently, the Patient-Assistant Relationship in terms of effective communication and emotional intelligence on the robot's part has been given emphasis. And this new approach is called Social Assistive Robotics, SAR, [8].

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 [3], [9], [14], [15], who continue the work of their innovative predecessors Pearl, MOVAID and Care-O-Bot.

Automatic speech recognition has resulted in more natural interaction between humans and robots. Human speech can be noisy and not straightforward in terms of the context and any system that interprets or produces human-robot dialogues must be able to perform efficiently even with noisy and stochastic speech. In [15], in the Spoken Dialog Management System Design which is a Partially Observable Markov Decision Process, POMDP, proposed by Pineau and Thrun in [5] is used, because a POMDP is a natural way of modelling dialog processes. The machine interpreter cannot have direct knowledge of the state of the user and it can only make conclusions about the patient's state from the noisy speech user data. The HPOMDP framework provides the mechanism for modelling uncertainty about what the user is trying to communicate [6]. The possible states that are modelled are the actions, transition probabilities, rewards, observations and observation probabilities that comprise the Hierarchical POMDP, HPOMDP.

Care-O-Bot, a mobile service robot, performs supporting tasks for patients that are in their home. Care-O-Bot also conducts Media management, for example Videophone, TV, stereo, Day-Time-Manager, time for medicine, communication with medical and public facilities, physician, hospital, clinic, authorities and supervision of vital signs and emergency call.

The Brian project focused on social intelligence to make robot assistants aware of the user's status through recognition of the user's pose and gestures. As a result, the robot is able to make better decisions and to complete the requested tasks. Moreover, it uses reinforcement learning and integrates emotions in the robot's behaviour to establish bi-directional social communication.

The SIRA robot project implements the same applications as the nursing assistant robot, Pearl, while also integrating the human-robot interaction, HRI, abilities including a 3D face, speech processing and dialogue management for recognition of affective speech and natural language.

Carnegie Mellon University in the U.S. designed and implemented a robotic nurse assistant, Pearl, and deployed it at a nursing home to assist older people and the nursing staff [2]. Pearl provides a walking aid, reminds patients of their medicine time and accompanies patients to destinations for appointments and events. As an improvement of HRI, Pearl uses an articulated head unit with facial expression on a visual display [4]. The software component developed for Pearl to provide the cognitive functions is called Autominder. Autominder has three main components: a Plan Manager, which stores the client's plan of daily activities, a Client Modeler, which uses information about the client's observable activities and a Personal Cognitive System, which can reason between what the client is supposed to do and what she is doing, and makes decisions about



when to issue reminders. As the elderly patient follows their daily routine, sensor information is collected by the assistant and sent to the Client Modeler. The Personal Cognitive System creates a reminder plan that is marginally optimum.

[44] paper reports a Wizard-of-Oz, WOZ, experiment for elderly in the home health care system. They collect dialogue examples of elderly users through the WOZ experiment and conduct a recognition experiment. The experimental result demonstrates that a user's response following a system's question tends to consist not bare Yes/No answer but content words without Yes/No word and that the performance of speech recognition is improved using WOZ data and experiment analysis results and conclusions.

AVATALK-Survey addresses survey nonresponse, a critical training need in survey research. AVATALK-Survey generates responses integrating a range of emotions implementing contextual. With Avatalk, patients can engage in unscripted conversations and see and hear their realistic responses. The main Avatalk components are a Language Processor and a Behavior Engine. The Language Processor maps the input to an underlying semantic representation and semantic representations to gestural and speech output. The Behavior Engine maps Language Processor output to behaviors which include decision making and problem solving, performing actions in the virtual world, and spoken dialogue. AVATALK virtual humans act realistically as if they are angry, depressed, serene, or in pain. Behaviour and Emotions are expressed through facial expression, lip synching, gesturing, choice of utterances, conversational expectancies, and branching logic.

1.3 Socially Intelligent Healthcare Robotic Assistants

It has to be noted that robotic assistants, which offer services of psychological enrichment to elderly people, is also a very active research field recently. These robotic assistants can improve physiological and psychological functioning, either by providing entertainment or by performing social stimulation to people. Furthermore, they can urge patients to more frequent social interaction either between them and their doctors and nurses or between them and their families and friends. For example, robots such as PARO and AIBO have been found to display similar therapeutic value to having animals as companions. They proved able to stimulate communication among elderly people in a nursing home through interaction as well as entertainment [15], [16].

As robots are engaged in health service applications, provide services and assistance, and even cooperate with humans, they have to be in position to engage in social interaction with the patients. Recent research has highlighted the importance of social intelligence and interaction in the area of Human-Robot Interaction.

HRI Studies: Up to now, most HRI studies and evaluations of social robots are based on small-scale experiments or theoretical considerations [17], [18], [19]. In eldercare facilities, many experiments have been conducted with PARO and Pearl robots [20], [21], [22] which quantified the positive reactions and results from the interaction between elderly people and robots but did not directly assess the acceptance of the technology. Studies are still needed for evaluating



the effects and influences of aspects of a robotic design including behaviour, appearance, perceived adaptability or social intelligence.

Recent studies on interaction with robots stress the importance of social intelligence [24], [36], [26], [27], [28], even more so in a healthcare and eldercare environments. In [19], Emotion Related Data Collection is performed, focusing on levels of Trust and Responsibility in the Robot Characteristics. A more social intelligent robot can interact easier and therefore be accepted easier. In [19] they conducted an experiment to collect a large amount of structured interaction data to investigate the influence of acceptance of a robot interface by elders. The objective of [19] is to describe methods, experiences and lessons learned from these experiments.

Research involving explicit tests of robots or agents with elderly users has been carried out by Wada et al. [29] and Shibata et al. [30]. These studies concerned the seal shaped robot Paro. The aim of this study was to observe the use of a robot in a setting described as "robot assisted activity" and to prove that elders felt more positive after a few sessions by measuring the moods of the participants with a face scale form and the Profile of Mood States questionnaire.

Another experiment that took place in an eldercare institution concerned a robot named Pearl as described by Pollack [32] and Pineau et al. [31]. The robot was used in open-ended interactions, delivering sweets guiding elders to the location of a physiotherapy department.

Related research in which acceptance did play a significant role is described by De Ruyter et al. [38]. It was about a robotic interface, the iCat made by Philips, which was tested in a Wizard of Oz experiment. The participants were exposed to an introvert and an extravert version of the iCat interface to see whether this difference in interaction would lead to different levels of acceptance. To measure acceptance, the UTAUT questionnaire, Unified Theory of Acceptance and the Use of Technology, [34]) was used. UTAUT is a model that incorporates several influences on acceptance of technology. The aim of the study was to find out to what extent participants would use the iCat at home after having interacted with it.

A widely used tool to evaluate social abilities is Gresham & Elliott's Social Abilities Rating System (SSRS) [35]. Although this tool usually is applied in social research, the five basic features Cooperation, Empathy, Assertion, Self-Control and Responsibility match the aspects found in Human-Robot Interaction literature on social, or sociable, robots and agents [36], [37]. Besides, these five also appear to be relevant abilities in De Ruyter et al. [38] and Markopoulos et al [31] and selected the following behavioral features to be integrated in the robot's behaviour :

- listening with attention
- being kind and pleasant as well as eager to help and able to complete tasks
- recording personal details about people and reminding them
- being expressive
- admitting possible mistakes

Most conventional emotion models have a limited ability to communicate with humans. Usually, a human being observes and judges the expressions of



Figure 1.3: Robots Take the Stage by Brett Davis in flickr.

the emotion model, and the recognition rate is the evaluation of the model. In [11], in communication between WAMOEBA-2 and humans, there is no scenario like this. The psychological impressions in humans change dynamically according to the behavior of the robot and/or the humans. The characteristics of WAMOEBA-2 communication are as follows

- Adaptability in real world: WAMOEBA-2, an independent and behavior-based robot, it is not needed that the environment must be standardized such as the movement of humans.
- Diversity of the ways to communicate: Human beings can communicate without special interface tools. Moreover, neither words nor gestures for communication are specified, and preliminary knowledge is not required
- Development of communication: Communication is developed according to the behavior of humans and WAMOEBA-2 in real-time. There is no "story" and/or "scenario" set beforehand by a designer
- It is believed that the "freedom degree" mentioned above (where humans are not restrained in communication with robots) is an important element in order to realize robot-human emotional communication.

In this work, our contribution is two-fold. We propose a new word representation and a Retrieval based algorithm that is based in Conditional Entropy and it is used to retrieve the suitable answer in a Dialogue communication when an Input is given. Additionally, a Model for Attitude Modelling and Attitude Change is proposed and tested on Dialogue data that regard the Healthcare system and specifically the communication between Patient and Robotic Assistant as well as between Patient and Doctor.

The following 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 Heirich Popitz's Powers is presented and finally, in the last part, we analyse and give the results from our experiments on Dialogue Data.



Chapter 2

Conditional Entropy Retrieval Based Model in Dialogue Systems

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

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. Many challenges in NLP involve: natural language understanding, enabling computers to derive meaning from human or natural language input; and others involve natural language generation. 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, whose theoretical underpinnings discouraged the sort of corpus linguistics that underlies the machine-learning approach to language processing[55]. 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[54], 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. The cache language models upon which many speech recognition systems now rely are examples of such statistical models. Such models are generally more robust when given unfamiliar input, especially input that contains errors, as is very common for real-world data, and produce more reliable results when integrated into a larger system comprising multiple subtasks. Finally, the latest trend applies Deep Learning on Natural Language Processing, with DeepMind one of the most widely known[56], currently belonging to Google. Recent research has increasingly focused on unsupervised and semi-supervised learning



algorithms. Such algorithms are able to learn from data that has not been hand-annotated with the desired answers, or using a combination of annotated and non-annotated data. Generally, this task is much more difficult than supervised learning, and typically produces less accurate results for a given amount of input data. However, there is an enormous amount of non-annotated data available, including, among other things, the entire content of the World Wide Web, which can often make up for the inferior results. We will propose an innovation based on Information Theory for Natural Language Processing [58], [59].

The other important aspect that we have to consider when designing an Assistant Robot is the notion of a Social Robot. In [48], Dautenhahn and Billard proposed the following definition: "Social robots are embodied agents that are part of a heterogeneous group: a society of robots or humans. They are able to recognize each other and engage in social interactions, they possess histories (perceive and interpret the world in terms of their own experience), and they explicitly communicate with and learn from each other." According to [46], the human characteristics of interaction which are desirable in the communication with Assistant Robots too are expressing and perceiving emotions, communicating with high-level dialogue, learning and recognizing models of other agents, establishing and maintaining social relationships, using natural cues, like gaze and gestures, exhibiting distinctive personality and character as well as learning or developing various social competencies. In order to develop Social Robots, researchers focused on different aspects of the robot. In [47], a series of human - alike face characteristics and movements as well as pacing in speech tries to resemble those of humans. Speech is also a highly effective method for communicating emotion through tones, pitches and pacing. Dialogue is a joint process of communication. It involves sharing of information (data, symbols, context) and control between two (or more) parties. Billard and Dautenhahn describe a number of experiments in which an autonomous mobile robot was taught a synthetic proto-language [49]. Steels has examined the hypothesis that communication is bootstrapped in a social learning process and that meaning is initially contextdependent[50], [51]. Natural language dialogue is determined by a set of factors ranging from the physical and perceptual capabilities of the participants, to the social and cultural features of the situation in which the dialogue is carried out. To what extent natural language dialogue interfaces for robots should be based on human-human dialogue is clearly an open issue[52]. Moreover, creating a robot that communicates at a human peer level using natural language remains a grand challenge. More specifically, when we focus in the verbal communication as we do in this work, and, moreover, when the Robot happens to be an Assistant Robot for patients, we strongly feel that the attitude of the Robot towards the patient should vary in friendliness. We use a new metric based on the Popitz Powers to apply different levels of friendliness in the communication of the Assistant Bot with the patients, depending on the patient's Sentiment expressions and Polarity and strength of the expressions as in [57].

Information Theory and more specifically Entropy have been applied before as we mentioned, [58]. 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 Maximization as stated in this work which states: The correct distribution $p(a,b)$ is that which maximizes entropy or uncertainty subject to the



constraints which represent evidence. However, since we deal 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 to the phrase A coming from the patient, we used the Criterion of the Minimization of the Joint Normalized Conditional Entropy $\frac{H(B/A)}{H(B)}$.

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 that need to be stored in memory?

Up to now, the representation of sentences was either a zero-one vector, according to which words appeared in each sentence, or a probabilistic vector representation based on word occurrences. 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, $\frac{H(B/A)}{H(B)}$, as a criterion, we should couple the 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 reply. So, now, our Word Representation 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 $\frac{H(C/A)}{H(C)}$ for all sentences C in our database and will return the sentence C that minimizes the Normalised Conditional Entropy $\frac{H(C/A)}{H(C)}$. 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, B or C are given by the following formulas that apply to Joint Entropies. If sentence A consists of words w_3, w_2 and sentence C consists of the words w_5, w_{10}, w_{25} then

$$\begin{aligned} \frac{H(C/A)}{H(C)} &= \frac{H(w_5, w_{10}, w_{25}/w_3, w_2)}{H(w_5, w_{10}, w_{25})} \\ &= \frac{-\sum_{k=0}^1 (p_k(w_5, w_{10}, w_{25}/w_3, w_2) \cdot \log p_k(w_5, w_{10}, w_{25}/w_3, w_2))}{-\sum_0^1 p_k(w_5, w_{10}, w_{25}) \cdot \log p_k(w_5, w_{10}, w_{25})} \end{aligned}$$

where in p_k k takes only 2 values, 0 or 1 as these are the only values present in the Adjacency Matrix ADJ.



At this point, we should note that whenever a sentence A comes up, certain words appear, w_5, w_{10}, w_{25} as we mentioned. These words have strong relations to many others in the Adjacency Matrix and hence in their representation such as common words in C and A or words that are connected to these words through different sentence interactions that have nothing to do with interaction C-A. In order to exclude those relationships and discriminate against them, we modified our formula further.

Let us denote the sentences space S and the words space W. If sentence A comes up in the dialogue, that means that all the other sentences in our database did not come up, that means that the event that is realised is not the event A but the event $A \cap (\overline{S - A})$. In the same way, when sentence C comes up, it means that all the other sentences in our database did not come up, it means that the event that is realised is not the event C but the event $C \cap (\overline{S - C})$.

$$\begin{aligned} & \frac{H(C, (\overline{S - C})) / A, (\overline{S - A})}{H(C, (\overline{S - C}))} \\ &= \frac{H((w_5, w_{10}, w_{25}), (\overline{W - (w_5, w_{10}, w_{25})}) / (w_{33}, w_2), (\overline{W - (w_{33}, w_2)}))}{H((w_{33}, w_2), (\overline{W - (w_{33}, w_2)}))} \end{aligned}$$

Figure 2.1: 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.



Chapter 3

Popitz Powers in Attitude Change Modeling for Dialogue Interaction

Attitude plays a significant role in human behaviour, communication and interaction as stated in [76]. Attitude can invoke emotions and most importantly urge to certain behaviour patterns [11]. This is the reason why Attitude Research in the Social Studies between humans should make the transition to the interaction between humans and robots. A good review of basic emotions and attitudes is [10]. Artificial attitude is used in social robots for several reasons. Artificial emotion can also provide feedback to the user, such as indicating the robot's internal state, goals and to an extent intentions [12]. Artificial attitude can act as a control mechanism, driving behaviour and reflecting how the robot is affected by, and adapts to, different factors over time [13]. The basic behavioural attitudes can be modelled with the help of

"In Phenomena of Power, the foundational theorist Heinrich Popitz treats power as an essential concept of the social sciences. Instead of striving for a power-free society, he argues, mankind should try to delimit power where possible and establish counter-power where necessary. Phenomena of Power delves into the socio-historical manifestations of power and breaks through to its general structures. Philosophically trained, historically informed, and endowed with the power of observation, Popitz uses everyday examples, such as how the passengers on a ship may organize their deckchairs, to illustrate his theory of power. He clearly articulates how the mechanisms of power taking and power stabilization work and how to track them in the social world" as stated in [76].

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 expressing 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



Figure 3.1: "Creepy Robot Friend" by Brett Davis in flickr

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 behaviour 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.

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 Attitude 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

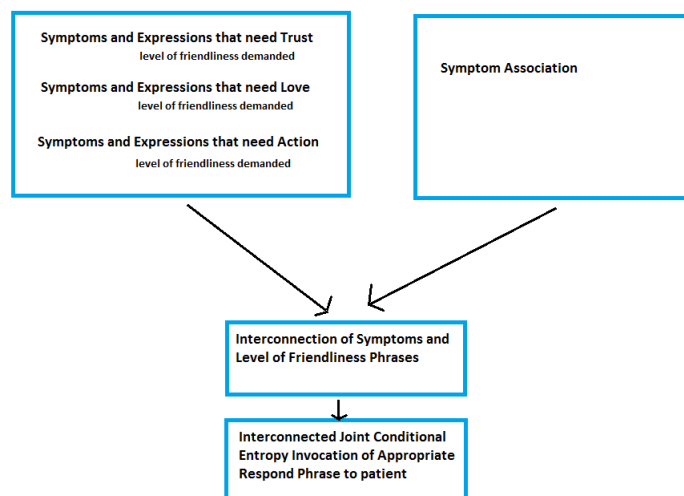


Figure 3.2: Proposed Procedure.

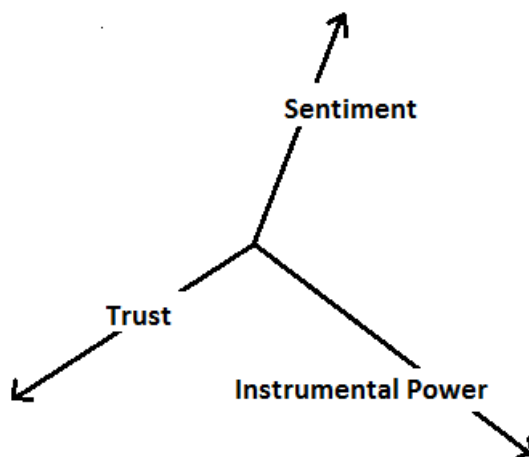


Figure 3.3: Trust, Sentiment and Instrumental Power vector Space Model.

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 in-



teractive 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 to Instrumental Power. The Attitude Change has also been studied by [77]. 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 subnetworks dialogues, Trust-Trust, Sentiment-Sentiment, Instrumental Power-Instrumental Power, we study the Conditional Information throughout Attitude Changes among these subnetworks.



Chapter 4

Experiments - Results

4.1 English Language Model Dialogues

In our first experiment where we wanted to test the Efficiency of the criterion for the Minimization of the Joint Normalized Conditional Entropy. The data that we used were 26 Conversations from [60] where sentence A was each sentence of each dialogue and sentence B was the next sentence after A.

We provide the Joint Normalized Conditional Entropy $\frac{H(C, (S-C))/1, (S-1))}{H(C, (S-C))}$ when the first sentence was given as input and all the other sentences C from the first dialogue were tested in Table 1. As we can see in Table 1, the value of the Joint Normalized Conditional Entropy is minimum for sentence 2 which is its proper reply and we already coupled sentence 1 and sentence 2 in that way in ADJ Adjacency Matrix.

We provide the dialogue from which we displayed these results in the Appendices as "Weather Dialogue".



Table 4.1: Joint Normalized Conditional Entropy when Sentence 1 was given.

sentence	$\frac{H(C/I)}{H(I)}$
1	0
2	0.9728019
3	1.032618
4	1.3564
5	1.76516
6	1.628056
7	2.024814
8	1.797272
9	1.090229
10	1.294418
11	1.294418
12	1.334918
13	2.274115
14	1.090229
15	1.332042
16	1.147255
17	2.169356
18	1.151982
19	1.151982
20	1.151982
21	1.635344
22	1.269823
23	1.028011
24	1.103319
25	1.028011
26	1.028011
27	1.028011
28	2.210161

4.2 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 Medical Lab of the Aristotle University of Thessaloniki which were an offer of Professor P.Bamidis and PhD Candidate A.Billis and also 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 regarded depression and were:

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

The dialogues 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, under the supervising of the social scientist of our team, Dr Hasanagas, 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-distracting 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 interconnected 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 which ones are combined with which ones in each sentence. 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, which practically means sentence K and the following response-sentence of the other party.

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 Table. 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

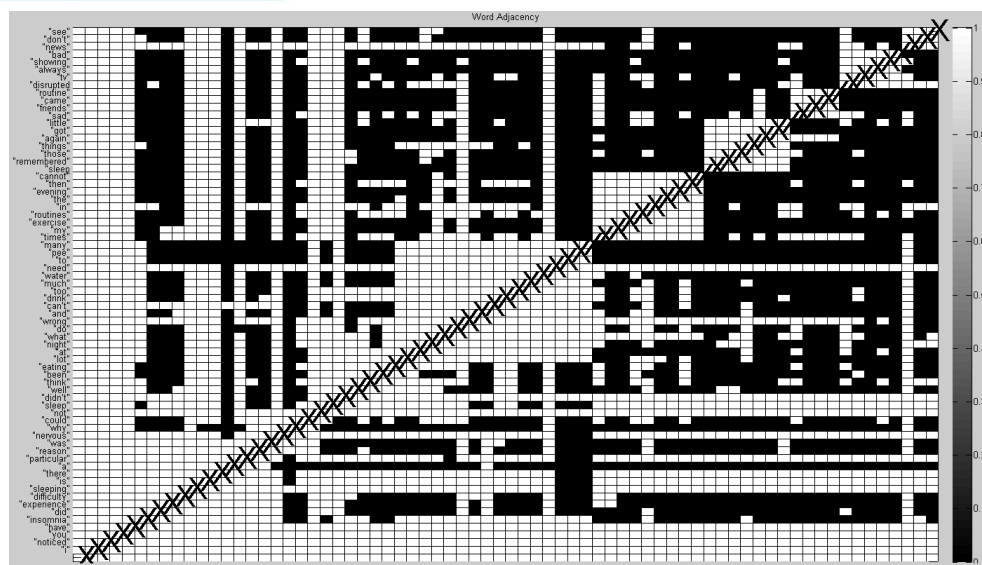


Figure 4.1: Word Adjacency Matrix for the 3 Dialogues.

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 first experiment.

Table 4.2: Success Rates in Conditional Entropy Retrieval Based Model, Deep Neural Networks and RBF Kernel SVM

Method	Success Rate %
Conditional Entropy	55.21
Deep NN	34.2
RBF Kernel SVM	26.41

In Figure4.2, we display the some results from the execution of the algorithm. As we can see, when the input to the system were phrases 23, 25, 26, 27, 28, 29, 30 or 31, the Conditional Entropy algorithm displayed minimum Entropy for the correctly most suitable phrases that correspond to each of the inputs, which are 23, 25, 26, 27, 28, 29, 30 and 31 responses.

In Figure4.3, we display the case of result 24 where phrase 24 was the input however the minimum Conditional Entropy, which gives us the suitable response, was estimated to be the property of response 12. Input phrase 24 and response 12 are displayed in Figure4.3 and we can see that they are not the perfect Complaint-Recommendation couple however they are still linked semantically.

In Figure4.4, we display the case of result where phrase "Why don't you try my pills! Get out of the way!" was the input. This phrase does not exist in the texts that the algorithm has access to. However, since it is asked, it chooses a suitable response with the help of the Conditional Entropy Retrieval method. The suitable response according to the algorithm is displayed under the input phrase and it is indeed once again connected semantically and up to a level logically.



```
R Console
[1] 0.12295499 0.12295499 0.12878093 0.12295499 0.12699147 0.12884185 0.12699147
[8] 0.12699147 0.12699147 0.12884185 0.12699147 0.12699147 0.12699147 0.12699147
[15] 0.12702201 0.12373551 0.11906069 0.12878093 0.11311352 0.10599209 0.08855129
[22] 0.12878093 0.12878093 0.12878093 0.12878093 0.12699147 0.12702201 0.12702201 0.12878093
[29] 0.12699147 0.12884185 0.12884185
> RES1[24,]
[1] 0.1244824 0.1320972 0.1470732 0.1320972 0.1379674 0.1423124 0.1423124 0.1423124
[8] 0.1320972 0.1244824 0.1372308 0.1072266 0.1477362 0.1320972 0.1453023 0.1473838
[15] 0.1439348 0.1453023 0.1477362 0.1473838 0.1372308 0.1379674 0.1439348 0.1477362
[22] 0.1477362 0.1477362 0.1473838 0.1470732 0.1423124 0.1379674 0.1379674
> RES1[25,]
[1] 0.1423124 0.1423124 0.1477362 0.1470732 0.1453023 0.1473838 0.1453023 0.1470732
[8] 0.1453023 0.1320972 0.1276565 0.1423124 0.1473838 0.1453023 0.1477362 0.1460943
[15] 0.1439348 0.1473838 0.1477362 0.1439348 0.1439348 0.1453023 0.1460943 0.1470732
[22] 0.1439348 0.1439348 0.1460943 0.1470732 0.1453023 0.1423124 0.1379674
> RES1[26,]
[1] 0.13292369 0.12948494 0.12948494 0.13459570 0.12948494 0.13469814 0.13292369
[8] 0.12948494 0.12948494 0.12402644 0.12702655 0.11620544 0.13459570 0.13292369
[15] 0.13292369 0.13338852 0.13469814 0.13459570 0.12948494 0.13338852 0.13459570
[22] 0.12948494 0.13338852 0.13292369 0.12702655 0.09330848 0.13469814 0.12948494
[29] 0.12402644 0.13292369 0.13292369
> RES1[27,]
[1] 0.11965894 0.10783335 0.12093276 0.10783335 0.10783335 0.11965894 0.11548802
[8] 0.11548802 0.11548802 0.10783335 0.10401666 0.11548802 0.11105075 0.11965894
[15] 0.11965894 0.11635179 0.10401666 0.11548802 0.11972646 0.11105075 0.10401666
[22] 0.11548802 0.11105075 0.11972646 0.11105075 0.11105075 0.07397012 0.11105075
[29] 0.12093276 0.11965894 0.12093276
> RES1[28,]
[1] 0.1228593 0.1158830 0.1228593 0.1076288 0.1076288 0.1158830 0.1228593 0.1228593
[8] 0.1207709 0.1076288 0.1158830 0.1076288 0.1225512 0.1225512 0.1207709 0.1201478
[15] 0.1158830 0.1225512 0.1158830 0.1201478 0.1158830 0.1228593 0.1158830
[22] 0.1201478 0.1228593 0.1201478 0.0834824 0.1099436 0.1207709 0.1201478
> RES1[29,]
[1] 0.11863085 0.10795567 0.11827991 0.09645311 0.10795567 0.11827991 0.11827991
[8] 0.11863085 0.11863085 0.10795567 0.09720609 0.11492433 0.11193947 0.11640959
[15] 0.11827991 0.11640959 0.11193947 0.10547147 0.10547147 0.11193947 0.11193947
[22] 0.11827991 0.11863085 0.11492433 0.10547147 0.11827991 0.11863085 0.09720609
[29] 0.06313583 0.11827991 0.11193947
> RES1[30,]
[1] 0.11414739 0.09707672 0.11414739 0.11414739 0.10796884 0.11656966 0.09707672
[8] 0.09707672 0.10796884 0.09707672 0.11249264 0.07984568 0.11656966 0.11656966
[15] 0.10796884 0.11656966 0.11586822 0.11656966 0.11249264 0.11249264 0.11249264
[22] 0.11414739 0.11249264 0.11656966 0.11656966 0.11249264 0.11656966 0.11586822
[29] 0.11656966 0.06505789 0.11656966
> RES1[31,]
[1] 0.1225512 0.1158830 0.1158830 0.1076288 0.1076288 0.1158830 0.1207709 0.1228593
[8] 0.1207709 0.1228593 0.1158830 0.1207709 0.1099436 0.1225512 0.1228593 0.1201478
[15] 0.1158830 0.1158830 0.1225512 0.1201478 0.1228593 0.1158830 0.1158830 0.1076288
[22] 0.1225512 0.1225512 0.1228593 0.1201478 0.1201478 0.1207709 0.0834824
> (25+9+19) / (2*31 + 34)
[1] 0.8520833
> line500[23]
[1] "i noticed you haven't met with someone or even talked to someone these last days i am not in a good mood to do anything"
> line600[42]
[1] "if you call them now you will be more stressed you can call them tomorrow"
```

Figure 4.2: Minimum Conditional Entropy cases.

```
[29] 0.12699147 0.12884185 0.12884185
> RES1[24,]
[1] 0.1244824 0.1320972 0.1470732 0.1320972 0.1379674 0.1423124 0.1423124 0.1423124
[8] 0.1320972 0.1244824 0.1372308 0.1072266 0.1477362 0.1320972 0.1453023 0.1473838
[15] 0.1439348 0.1453023 0.1477362 0.1473838 0.1372308 0.1379674 0.1439348 0.1477362
[22] 0.1477362 0.1477362 0.1473838 0.1470732 0.1423124 0.1379674 0.1379674
> RES1[25,]
[1] 0.1423124 0.1423124 0.1477362 0.1470732 0.1453023 0.1473838 0.1453023 0.1470732
[8] 0.1453023 0.1320972 0.1276565 0.1423124 0.1473838 0.1453023 0.1477362 0.1460943
[15] 0.1439348 0.1473838 0.1477362 0.1439348 0.1439348 0.1453023 0.1460943 0.1470732
[22] 0.1439348 0.1439348 0.1460943 0.1470732 0.1453023 0.1423124 0.1379674
> RES1[26,]
[1] 0.13292369 0.12948494 0.12948494 0.13459570 0.12948494 0.13469814 0.13292369
[8] 0.12948494 0.12948494 0.12402644 0.12702655 0.11620544 0.13459570 0.13292369
[15] 0.13292369 0.13338852 0.13469814 0.13459570 0.12948494 0.13338852 0.13459570
[22] 0.12948494 0.13338852 0.13292369 0.12702655 0.09330848 0.13469814 0.12948494
[29] 0.12402644 0.13292369 0.13292369
> RES1[27,]
[1] 0.11965894 0.10783335 0.12093276 0.10783335 0.10783335 0.11965894 0.11548802
[8] 0.11548802 0.11548802 0.10783335 0.10401666 0.11548802 0.11105075 0.11965894
[15] 0.11965894 0.11635179 0.10401666 0.11548802 0.11972646 0.11105075 0.10401666
[22] 0.11548802 0.11105075 0.11972646 0.11105075 0.11105075 0.07397012 0.11105075
[29] 0.12093276 0.11965894 0.12093276
> RES1[28,]
[1] 0.1228593 0.1158830 0.1228593 0.1076288 0.1076288 0.1158830 0.1228593 0.1228593
[8] 0.1207709 0.1076288 0.1158830 0.1076288 0.1225512 0.1225512 0.1207709 0.1201478
[15] 0.1158830 0.1225512 0.1158830 0.1201478 0.1158830 0.1228593 0.1158830
[22] 0.1201478 0.1228593 0.1201478 0.0834824 0.1099436 0.1207709 0.1201478
> RES1[29,]
[1] 0.11863085 0.10795567 0.11827991 0.09645311 0.10795567 0.11827991 0.11827991
[8] 0.11863085 0.11863085 0.10795567 0.09720609 0.11492433 0.11193947 0.11640959
[15] 0.11827991 0.11640959 0.11193947 0.10547147 0.10547147 0.11193947 0.11193947
[22] 0.11827991 0.11863085 0.11492433 0.10547147 0.11827991 0.11863085 0.09720609
[29] 0.06313583 0.11827991 0.11193947
> RES1[30,]
[1] 0.11414739 0.09707672 0.11414739 0.11414739 0.10796884 0.11656966 0.09707672
[8] 0.09707672 0.10796884 0.09707672 0.11249264 0.07984568 0.11656966 0.11656966
[15] 0.10796884 0.11656966 0.11586822 0.11656966 0.11249264 0.11249264 0.11249264
[22] 0.11414739 0.11249264 0.11656966 0.11656966 0.11249264 0.11656966 0.11586822
[29] 0.11656966 0.06505789 0.11656966
> RES1[31,]
[1] 0.1225512 0.1158830 0.1158830 0.1076288 0.1076288 0.1158830 0.1207709 0.1228593
[8] 0.1207709 0.1228593 0.1158830 0.1207709 0.1099436 0.1225512 0.1228593 0.1201478
[15] 0.1158830 0.1158830 0.1225512 0.1201478 0.1228593 0.1158830 0.1158830 0.1076288
[22] 0.1225512 0.1225512 0.1228593 0.1201478 0.1201478 0.1207709 0.0834824
> (25+9+19) / (2*31 + 34)
[1] 0.8520833
> line500[23]
[1] "i noticed you haven't met with someone or even talked to someone these last days i am not in a good mood to do anything"
> line600[42]
[1] "if you call them now you will be more stressed you can call them tomorrow"
```

Figure 4.3: Incorrect sample 24 and returned response from the algorithm. The response is not the optimum but it is still linked semantically to the input.



```
[1] 31
> RES1
      [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]      [,8]
[1,] 0.1078371 0.1144451 0.09140161 0.1125349 0.1125349 0.100702 0.1078371 0.100702
      [,9]      [,10]     [,11]     [,12]     [,13]     [,14]     [,15]
[1,] 0.1078371 0.1125349 0.05249352 0.1144451 0.05249352 0.100702 0.1078371
      [,16]     [,17]     [,18]     [,19]     [,20]     [,21]     [,22]
[1,] 0.06713464 0.05249352 0.100702 0.05249352 0.06713464 0.05249352 0.1125349
      [,23]     [,24]     [,25]     [,26]     [,27]     [,28]     [,29]     [,30]
[1,] 0.05249352 0.1125349 0.100702 0.100702 0.09140161 0.0801533 0.100702 0.1078371
      [,31]
[1,] 0.1078371
> t(RES1)
      [,1]
[1,] 0.10783707
[2,] 0.11444512
[3,] 0.09140161
[4,] 0.11253493
[5,] 0.11253493
[6,] 0.10070196
[7,] 0.10783707
[8,] 0.10070196
[9,] 0.10783707
[10,] 0.11253493
[11,] 0.05249352
[12,] 0.11444512
[13,] 0.05249352
[14,] 0.10070196
[15,] 0.10783707
[16,] 0.06713464
[17,] 0.05249352
[18,] 0.10070196
[19,] 0.05249352
[20,] 0.06713464
[21,] 0.05249352
[22,] 0.11253493
[23,] 0.05249352
[24,] 0.11253493
[25,] 0.10070196
[26,] 0.10070196
[27,] 0.09140161
[28,] 0.08015330
[29,] 0.10070196
[30,] 0.10783707
[31,] 0.10783707
> C(RES1)
[1] "why don't you try my pills get out of my way"
> lines600(1)
[1] "if you do not take the initiative to take a walk or talk to someone your mood will not change"
> |
```

```
all(nrow(yh)){
  yh )
  WE)
  in 1:wek[1]) {#-----
  in 1:wek[2]) {#-----
  ,nn1)>0) WE[nn1,nn1]<-0}#-----
  ,nn1]<1) WE[nn1,nn1]<-1}#-----
  --
  --
  (yh,WE) #-----
  (xh,WE) #-----

check them like this, what does the answer you just gave have to add to the answer question chind?
Joint_TransferE(t(W80[x, ]), t(W80[y, ]))
# x question, y answer
ruk1)
Joint_TransferE(t(W80[y, ]), t(W80[x, ]))
ruk1)
Joint_TransferE(t(W80[y, ]), t(W80[x, ])) # this info to answer H(Y/X) / H(Y)
buk2)
Joint_TransferE(xh,yh) # and this has to be the minimum , H(X/Y) / H(X)
k3)
Joint_TransferE(xh,yh) # and this has to be the minimum , H(X/Y) / H(X)
Joint_TransferE(yh,xh) # auto, and this has to be the minimum , H(X/Y) / H(X)
k3=buk4)
k4)
Joint_TransferE(xh,yh) # auto, and this has to be the minimum , H(X/Y) / H(X)
buk4)
Joint_TransferE(t(W80[x, ]), t(W80[y, ])) # this info to answer H(Y/X) / H(Y)
Joint_TransferE(t(W80[y, ]), t(W80[x, ])) # this info to answer H(Y/X) / H(Y)
k1)
buk4)
Joint_TransferE(t(W8000[x, ]), t(W8000[y, ])) # and this has to be the minimum , H(X/Y) / H(X)
ruk3)
```

Figure 4.4: Suitable Response returned by the Conditional Entropy Retrieval Model to our input sentence that is not present in the database.



4.3 Attitude Change Flow in "Good Doctor"- "Bad Doctor" Dialogues

For this last experiment, the Dialogues of two Doctor-Patient Interaction videos were recorded. The Videos were created by the Medical Lab of the Aristotle University of Thessaloniki and their aim was to videotape one Medical Examination where the Doctor 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. In the next step, we created the three Attitude variations, Trust, Sentiment and Instrumental 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 every time an Attitude Change takes 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.

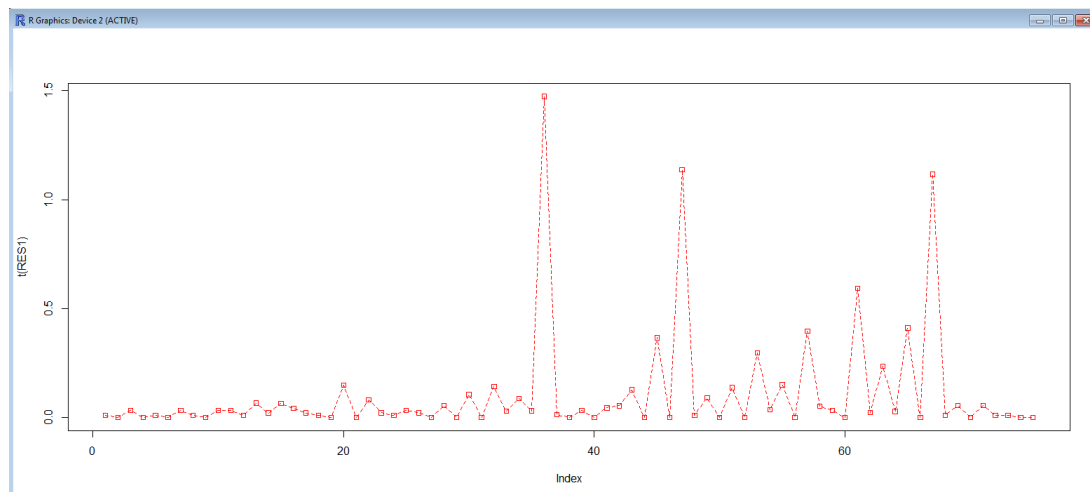
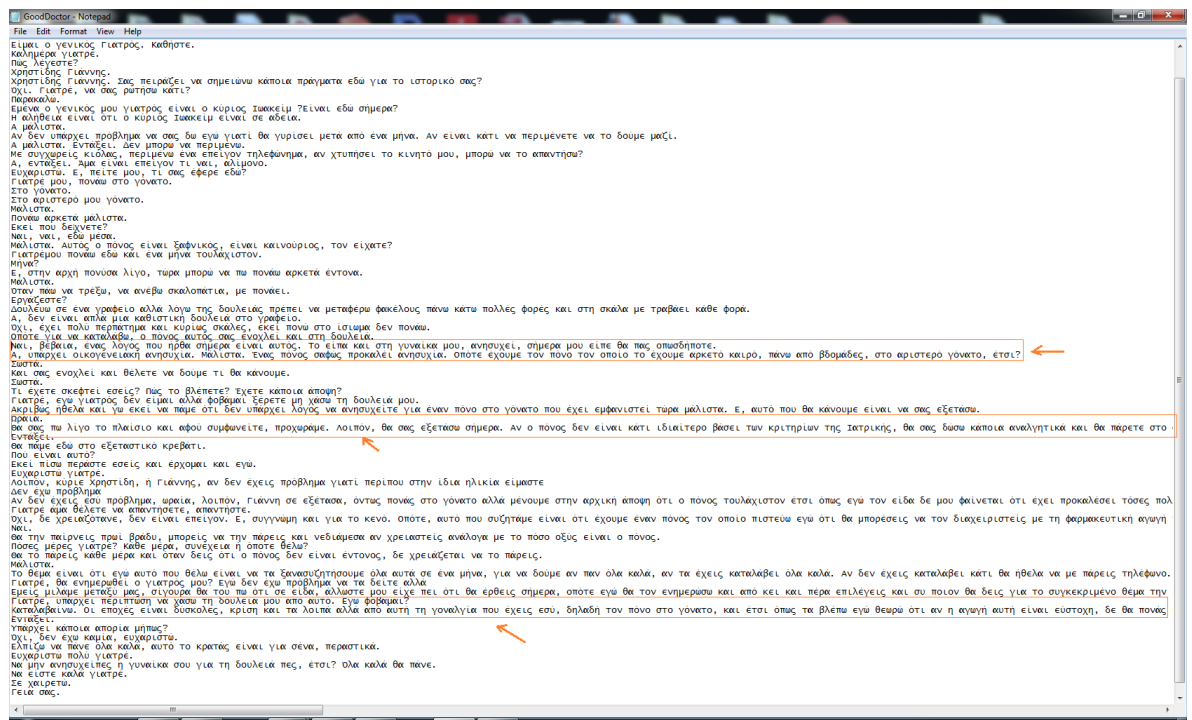


Figure 4.5: Good Doctor Dialogue Conditional Entropy Flow

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

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

We notice that the Bad Doctor Dialogue displays more Attitude Changes which also seem to be bigger in terms of Conditional Entropy measure. On the other hand, the Good Doctor Dialogue seems to flow without many variations in attitude and with peaks that are lower. All in all, it should be noted that since the words in the word network were connected through interactive phrases, stimulation-response, for every attitude of the three, Trust, Sentiment or Instrumental Power, we expect Conditional Entropy to be smaller when there is an accordance in Attitude in the stimulation and the response and an increase in the Conditional Entropy when there is an inaccordance. An inaccordance may be a



case for example when one agent of the dialogue chooses a phrase with an Attitude of Trust and the other agent responds abruptly, disrupting the conversation and maybe showing anger, so we have an interaction of Trust-Instrumental

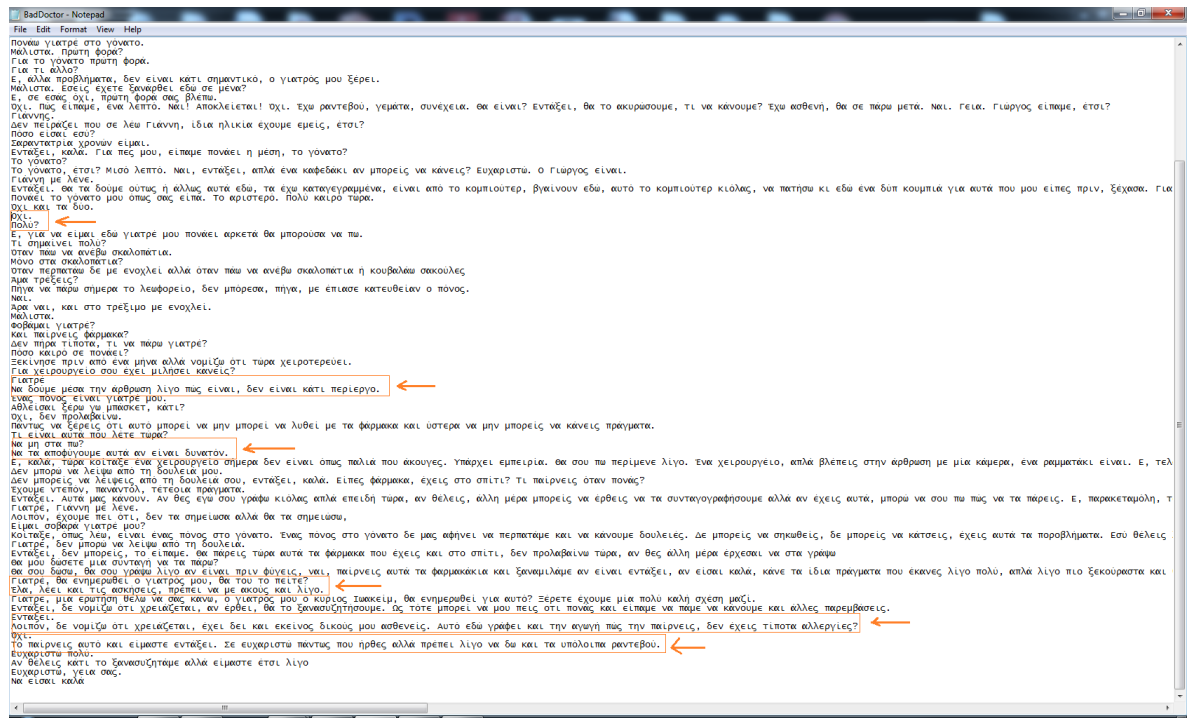


Figure 4.8: Phrases where Peaks of Conditional Entropy take place.

Power. Another example is when an agent addresses a phrase of Instrumental Power, like a warning, and the response has an attitude of Sentiment where the other agent becomes sentimental and starts complaining. In this case we have an interaction of the form Instrumental Power-Sentiment where the Conditional Entropy is again expected to have a higher value. This expectation coincides with the above results that we displayed in the Conditional Entropy Flow for all the pairs of phrases in the dialogue, phrase1-phrase2, phrase2-phrase3 and so on, where the pairs of phrases that have inaccordance in Attitude, tend to exhibit larger values of Normalised Conditional Entropy while the pairs of phrases that have accordance in Attitude, tend to exhibit smaller values of Normalised Conditional Entropy.



Chapter 5

Conclusions

In this work, we derived a new Retrieval Based model based on Normalised Conditional Entropy which was applied to Dialogue data that regard the interaction of Patients and Robotic Assistants. Our experiment showed that they outperform the Retrieval Based models that are currently used which are Deep Neural Networks and Support Vector Machines. Moreover, three possible types of Attitudes were defined in Dialogue Interaction which were based on three Popitz Powers, Trust, Love and Action. The three Attitudes that we deployed are Trust, Sentiment and Instrumental Power. Using the Conditional Entropy Retrieval Based model that we proposed, we recorded the Attitude Changes in the pairs of Dialogue phrases in two Patient-Doctor Dialogues. The Conditional Entropy Flows that we recorded proved that the phrases where Attitude Changes take place and there is an inaccordance in Attitude between the stimuli and the response, tend to exhibit higher values of Conditional Entropy. Also, throughout the Dialogues, when there is a Good communication between the Doctor and the patient the Conditional Entropy Flow is more smooth in contrast to bad Doctor-Patient Communication where there are more Attitude changes and greater variability in the Conditional Entropy of the phrases.



Bibliography

- [1] Designing a robotic assistant for healthcare applications, Tony Kuo, Elizabeth Broadbent and Bruce MacDonald.
- [2] Pineau J, Montemerlo M, Pollack M, Roy N and Thrun S. Towards robotic assistants in nursing homes: Challenges and results. Special issue on Socially Interactive Robots, Robotics and Autonomous Systems. 2003; 42: 271-281.
- [3] Nejat G, Ficocelli M. Can I be of assistance? The intelligence behind an assistive robot. In: Proc. IEEE International Conference on Robotics and Automation ICRA 2008. p. 3564-3569.
- [4] Pearl: A Mobile Robotic Assistant for the Elderly, Martha E. Pollack, Laura Brown, Dirk Colbry, Cheryl Orosz, Bart Peintner, Sandra Engberg, Judith T. Matthews, Jacqueline Dunbar-Jacob, Colleen E. McCarthy, Sebastian Thrun, Michael Montemerlo, Joelle Pineau, Nicholas Roy, AAI Technical Report WS-02-02.
- [5] J. Pineau and S. Thrun. "Hierarchical POMDP Decomposition for A Conversational Robot". Carnegie Mellon University. Robotics Institute.
- [6] N. Roy, J. Pineau and S. Thrun. "Spoken Dialog Management for Robots". Robotics Institute, Carnegie Mellon University.
- [7] Heerink, M., Krose, B., Wielinga, B., Evers, V. Human-Robot User Studies in Eldercare: Lessons Learned. In: Proceedings ICOST, Belfast; 2006. p. 31-38.
- [8] Heerink M, Krose B, Evers V, Wielinga B. The Influence of a Robot's Social Abilities on Acceptance by Elderly Users. In: Krose B, editor. Proc. 15th IEEE International Symposium on Robot and Human Interactive Communication ROMAN; 2006. p. 521-526.
- [9] Kang KI, Mataric MJ. A hands-on physical therapy assistance robot for cardiac patients. In: International Conference of Rehabilitation Robotics (ICORR); 2005. p. 337-340.
- [10] P. Ekman, "Basic emotions", in: T. Dalgleish, M. Power (Eds.), Handbook of Cognition and Emotion, Wiley, New York, 1999.
- [11] T. Ogata, S. Sugano. "Emotional communication robot: WAMOEBA-2R emotion model and evaluation experiments". Proceedings of the International Conference on Humanoid Robots, 2000.



- [12] C. Bartneck, M. Okada. "Robotic user interfaces". Proceedings of the Human and Computer Conference, 2001.
- [13] F. Michaud, et al.,. "Artificial emotion and social robotics". Proceedings of the International Symposium on Distributed Autonomous Robotic Systems, 2000.
- [14] Lopez ME, Bergasa LM, Barea R, Escudero MS. A Navigation System for Assistant Robots Using Visually Augmented POMDPs. Autonomous Robots. 2005 Jul; 19(1):67-87.
- [15] Barea R, Bergasa LM, Lopez E, Escudero MS, Leon C. Face Recognition for Social Interaction with a Personal Robotic Assistant. In: Proc. EUROCON 2005. The International Conference on Computer as a Tool. vol. 1; 2005. p. 382-385.
- [16] Tamura T, Yonemitsu S, Itohj A, Oikawa D, Kawakami A, Higashi Y, Fugimooto T and Nakajima K. Is an Entertainment Robot Useful in the Care of Elderly People With Severe Dementia? J Gerontol A Biol Sci Med Sci. 2004; 59: 83-85.
- [17] Birgit G, Matthias H, and Rolf S. Care-o-bot II: Development of a next generation robotic home assistant, Autonomous Robots. 2004; 16: 193-205.
- [18] Lay K, Prassler E, Dillmann R, Grunwald G, Hagele M, Lawitzky G, Stopp A and von Seelen W. MORPHA: communication and interaction with intelligent, anthropomorphic robot assistants. IEEE transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews. 2004 May; 34(2): 113-124.
- [19] Heerink, M., Krose, B., Wielinga, B., Evers, V. Human-Robot User Studies in Eldercare: Lessons Learned. In: Proceedings ICOST, Belfast; 2006. p. 31-38.
- [20] Pineau J, Montemerlo M, Pollack M, Roy N and Thrun S. Towards robotic assistants in nursing homes: Challenges and results. Special issue on Socially Interactive Robots, Robotics and Autonomous Systems. 2003; 42: 271-281.
- [21] Wada K, Shibata T, Saito T, Tanie K. Effects of robot assisted activity to elderly people who stay at a health service facility for the aged. In: Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS. Vol. 3; 2003. p. 2847-2852.
- [22] Shibata T, Wada K, Tanie K. Statistical analysis and comparison of questionnaire results of subjective evaluations of seal robot in Japan and UK. In: Proc. IEEE International Conference on Robotics and Automation ICRA '03. vol. 3; 2003. p. 3152-3157.
- [23] Fritsch WB J, Sagerer G. Bringing it all together: Integration to study embodied interaction with a robot companion. In: AISB 2005 Symposium ? Robot Companions: Hard Problems and Open Challenges in RobotHuman Interaction; 2005.



- [24] Duffy, B.R. Anthropomorphism and The Social Robot. Robotics and Autonomous Systems, march (2003): 170-190.
- [25] Breazeal, C., Towards sociable robots, Robotics and Autonomous Systems 42.3-4: 167-175, 2003.
- [26] Breazeal, C., Socially intelligent robots, Interactions, Volume 12 Issue 2: 19 ? 22, 2005.
- [27] Dautenhahn, K., Ogden, B., and Quick, T., From embodied to socially embedded agents?implications for interactionaware robots, Cognitive Systems Research (3), 2002.
- [28] Forlizzi, J. Robotic products to assist the aging population . Interactions, volume 12 Issue 2, 2005.
- [29] Wada, K., Shibata, T., Saito, T. and Tanie, K., Effects of Robot Assisted Activity to Elderly People who Stay at a Health Service Facility for the Aged. Proceedings of the 2003 IEEE/RSJ Intl. Conference on Intelligent Robots and Systems, Las Vegas, Nevada, October 2003.
- [30] Shibata, T, Wada, K., and Tanie, K., Statistical Analysis and Comparison of Questionnaire Resultsof Subjective Evaluations of Seal Robot in Japan and U.K.. Proceedings of the 2003 IEEE International Conference on Robotics & Automation 2003.
- [31] Pineau, J., Montemerlo, M., Pollack, M., Roy, N. and Thrun, S. Towards robotic assistants in nursing homes: Challenges and results. Robotics and Autonomous Systems 42 (2003): 271-281. 2003.
- [32] Pollack, M., Brown, L., Colbry, D., Orosz., C., Peintner, B., Ramakrishnan, S., Engberg, S., Matthews, J., Dunbar-Jacob, J. and McCarthy, C. Pearl: A Mobile Robotic Assistant for the Elderly. AAAI Workshop on Automation as Eldercare. 2002.
- [33] De Ruyter, B., Saini, P., Markopoulos., P. and Van Breemen, A.J.N. Assessing the Effects of Building Social Intelligence in a Robotic Interface for the Home. Interacting with Computers, Volume 17, Issue 5, 1 September 2005, 522-541. 2005.
- [34] Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. User Acceptance of Information Technology: Towards a Unified View. MIS Quaterly, 27(3), 425-478, 2003.
- [35] Gresham, F. M., and Elliot, S. N. Social abilities rating system. Manua. Circle Pines: American Guidance Service, 1990.
- [36] Breazeal, C., Towards sociable robots, Robotics and Autonomous Systems 42.3-4: 167-175, 2003.
- [37] Dautenhahn, K. Roles and functions of robots in human society: implications from research in autism therapy. Robotica, Volume 21 Issue 4 august 2003.



- [38] De Ruyter, B., Saini, P., Markopoulos., P. and Van Breemen, A.J.N. Assessing the Effects of Building Social Intelligence in a Robotic Interface for the Home. *Interacting with Computers*, Volume 17, Issue 5, 1 September 2005, 522-541. 2005.
- [39] Wizard of Oz Experiments, M. Hajdinjak and F. Mihelic, *melitah-eurocon03*.
- [40] N.M. Fraser, G.N. Gilbert. *Simulating Speech Systems*. *Computer Speech and Language*, 5(1): 81-99, 1991.
- [41] N. Dahlback, A. Jonsson, L. Ahrenberg. Wizard of Oz studies: why and how. *Proceedings of the international workshop on Intelligent user interfaces*, 193-200, USA 1993.
- [42] M. Eskenazi, A. Rudnick, K. Gregory, P. Constantinides, R. Brennan, C. Bennett, J. Allen. *Data Collection and Processing in the Carnegie Mellon Communicator*. *Proceedings of the 6th European Conference on Speech Communication and Technology*, 6: 2695-2698, Hungary 1999.
- [43] Design of the VICO Spoken Dialogue System: Evaluation of User Expectations by Wizard-of-Oz Experiments, Petra Geutner, Frank Steffens and Dietrich Manstetten.
- [44] Dialogue Experiment for Elderly People in Home Health Care System, Shin-ya Takahashi, Tsuyoshi Morimoto, Sakashi Maeda and Naoyuki Tsuruta.
- [45] S. Takahashi, T. Morimoto, S. Maeda, and N. Tsuruta: Spoken dialogue system for home health care. In: *Proc. of ICSLP*. Volume 4. (2002) 2709-2712.
- [46] A Survey of Socially Interactive Robots: Concepts, Design, and Applications, Terrence Fong, Illah Nourbakhsh and Kerstin Dautenhahn, *CMU – RI – TR – 02 – 29*.
- [47] Toward Sociable robots, Cynthia Breazeal, *Robotics and Autonomous systems*, 42, 2003, 167 – 175.
- [48] K. Dautenhahn and A. Billard, Bringing up robots or - the psychology of socially intelligent robots: from theory to implementation, in: *Proceedings of Autonomous Agents*, 1999.
- [49] A. Billard and K. Dautenhahn, Grounding communication in situated, social robots, in: *Proceedings of Towards Intelligent Mobile Robots Conference*, Report UMCS-97-9-1, Department of Computer Science, Manchester University, 1997.
- [50] L. Steels, AIBO's first words. The social learning of language and meaning, in: H. Gouzoules, ed., *Evolution of Communication* 4(1), Amsterdam, John Benjamins Publishing Company, 2001.
- [51] 1] L. Steels, Language games for autonomous robots, *IEEE Intelligent Systems* 16 (5) (2001).



- [52] K. Severinson-Eklund et al., Social and collaborative aspects of interaction with a service robot, Special Issue on Socially Interactive Robots, Robotics and Autonomous Systems 42 (3-4) (2003).
- [53] On Natural Language Dialogue with Assistive Robots, Vladimir A. Kulyukin Computer Science Assistive Technology Laboratory Department of Computer Science Utah State University.
- [54] Towards a Robotic Dialogue System with Learning and Planning Capabilities, Karolina Eliasson, 4th IJCAI Workshop on Knowledge and Reasoning in Practical Dialogue Systems.
- [55] Olivier Lemon, Olivier Pietquin. Machine Learning for Spoken Dialogue Systems. European Conference on Speech Communication and Technologies (Interspeech'07), Aug 2007, Anvers, Belgium. pp.2685-2688, 2007.
- [56] <https://deepmind.com/>
- [57] Sentiment Analysis: Capturing Favorability Using Natural Language Processing, Tetsuya Nasukawa and Jeonghee Yi.
- [58] A Simple Introduction to Maximum Entropy Models for Natural Language Processing, Adwait Ratnaparkhi, IRCS Report 97-08.
- [59] Foundations of Statistical Natural Language Processing, Christopher D. Manning and Hinrich Schutze.
- [60] Conversations for all Occasions, Natalie Xuan Van, Yen Chau Van, Ai Chau Hoang and Hung Hoang.
- [61] Popitz, H., 1992, Phaenomene der Macht, ed Tübingen, J.C.B. Mohr (Paul Siebeck).
- [62] Wizard of Oz Experiments for Companions, Jay Bradley, Oli Mival, David Benyon.
- [63] Creation of a Doctor-Patient Dialogue Corpus Using Standardized Patients, Robert S. Belvin, Win May, Shrikanth Narayanan, Panayiotis Georgiou and Shadi Ganjavi, HRL Laboratories, LLC.
- [64] Interactive Soft Skills Training using Responsive Virtual Human Technology, Robert C. Hubal and Curry I. Guinn.
- [65] The Virtual Pediatric Standardized Patient Application, Robin Deterding, Cheri Milliron and Robert Hubal.
- [66] The Repurposing Existing Virtual Patients Project, REViP, Chara Balasubramaniam and Terry Poulton, St George's, University of London, Heidelberg University, Critical Friend Group: University of Central Lancashire, and University of Chester.
- [67] The virtual patient project: Using low fidelity, student generated online cases in medical education, Michelle Imison and Chris Hughes, Proceedings Ascilite Melbourne 2008.



- [68] Virtual Patient Simulation at U.S. and Canadian Medical Schools, Grace Huang, MD, Robby Reynolds, MPA, and Chris Candler, MD.
- [69] <http://www.medbiq.org/>
- [70] Sorting Out the virtual Patient, How to Exploit artificial intelligence, Game Technology and Sound Educational Practices to Create Engaging Role-Play Simulations, Thomas B.Albot, Kenji Sangae, Bruce John, Albert A.Rizzo, International Journal of Gaming and Computer-Mediated Simulations, 1-19, July-September 2012.
- [71] https://en.wikipedia.org/wiki/Virtual_patient#cite_note-1
- [72] University of Exeter. "Negative patient-doctor communication could worsen symptoms." ScienceDaily. ScienceDaily, 27 January 2015.
- [73] https://en.wikipedia.org/wiki/Doctor%E2%80%93patient_relationship
- [74] Walker, Jan, et al. "Insights for internists:"I want the computer to know who I am". Journal of general internal medicine 24.6 (2009): 727-732.
- [75] Cimino, James J., Vimla L. Patel, and Andre W. Kushniruk. "What do patients do with access to their medical records?." Studies in health technology and informatics 2 (2001): 1440-1444.
- [76] Leading in Physical Education, Theoretical Approach and Practical Considerations, A.Bekiari and N.Hasanagas, Kyriakidis Bros Publications S.A.
- [77] Compliance, Identification, and Internalization: Three processes of attitude change HC Kelman, Journal of Conflict Resolution, 1958.



Chapter 6

Appendix

6.1 Weather Dialogue

Oh, it feels so cold this morning.

It sure is. Early this morning my car's windshield was covered with frost. I had to spray it with water before I could head to school.

Who would have thought it could be this cold in early December, especially in California.

I know. The temperature was 35 degrees Fahrenheit when I woke up this morning. I was freezing as soon as I got out of bed. The cold weather just hit me by surprise.

I cannot remember when it was this cold in early December.

Brace yourself for the rain this afternoon. Cold and wet, Yuck!

It is going to rain this afternoon?

Not only this afternoon, but also the rest of the week.

Oh, it is going to be miserable. I have a full class schedule today and tomorrow. To walk from class to class, I will have to juggle my books and my umbrella trying not to get wet. You carry too many books. Why don't you leave some of them in your locker?

My locker is a long way from my English classes. This is the reason why I carry all my books with me. Is it going to rain hard or just drizzle?

The news said that it would start to drizzle around noon, and then it would rain really hard by three o'clock.

No hope for better weather this week?

There is a slim chance of sunshine by Saturday. However, it will be foggy, windy, and rainy before the sun comes out this weekend.

I am glad that it rains even though I do not like rainy weather. We have a very dry season so far this year.

Yes, I can hardly remember when it rained last time. Well, as long as there is no thunder or lightning, I can bear it.

We rarely have thunder or lightning in California.

We are very lucky that California has one of the best weather conditions in America. When it is hot, it is not humid; when it rains, there is no thunder or lightning, and the cold weather during the winter season is quite mild compared to the weather of the other states.

Yes, we are lucky. However, sometimes when I look at the Christmas pictures, I just wish we had some snow. It looks so pretty when everything is covered by a blanket of pure white snow.

Living in southern California all my life, I have never seen snow. I would not mind playing in the snow once in a while.

Yes, it would be fun to make a snowman or go skiing.

We have never seen snow; we have never made a snowman, and we have never gone skiing. We better do something



about this.

May be we should plan a trip to Aspen, Colorado during winter break. I heard that the skiing season is fantastic up there.

I don't think we can afford a trip to Aspen. It is very expensive up there.

I am just wishing. I know what I will be doing during winter break. I will be working very hard to save money for a new car.

With the cars that we drive, it is better that we live in a place where there is no snow. You are right, we are better off with no snow. Ok, I have class right now; see you later in the library.

See you later.

6.2 Trust-Trust Complaint-Recommendation Interactions

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 your 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.

6.3 Sentiment-Sentiment Complaint-Recommendation Interactions

I noticed you have insomnia. Did you experience difficulty sleeping? I am going to collapse. I will soon start crying. You can take deep breaths and drink a nice glass of milk or Louiza tea. You can read your favourite book or take a nice warm bath.

I noticed you have insomnia. Is there a reason why you didn't sleep well? I cannot stop eating. My boulimia kicked in.

We should always care about ourselves and don't eat coffee, alcohol or eat too much 3 hours before you go to sleep.

I noticed you have insomnia. Why am I so thirsty? I cannot stop drinking water.

It is better if you drink water earlier before going to bed.

I noticed you have insomnia. Is there a reason why you didn't sleep well?

Exercising in the evening exhausted me and I cannot sleep at all. Your body needs some hours to relax before going to sleep. Why don't you try exercising earlier?

I noticed you have insomnia. Is there a reason why you didn't sleep well? I can never forget those things. I think I will start crying.

What is your most happy thing you can think before bed?

I noticed you have insomnia. Is there a reason why you didn't sleep well?

My friends didn't let me rest all day. You can always take care of yourself doing the same things every day.

I noticed you have insomnia. Is there a reason why you didn't sleep well? Don't you see what is happening to the world?

I know TV is like that but why can't you try something more relaxing?

I noticed you have insomnia. Is there a reason why you can't sleep? I am sweating like there's no tomorrow. Do you want to lower the room temperature wear something lighter? If you want you can drink a cool glass of milk or water take a nice shower.

I noticed you have insomnia. Is there a reason why you can't sleep? My back is killing me!

In which position is your body more comfortable? Do you need a painkiller?

I noticed you have insomnia. Have you started a new drug recently? How can I sleep if they keep changing the pills every day?

Did you think about medication side-effects? Do you want to discuss it with your doctor?

Have you been crying? My heart sunk.

You know that there are people who care about you. Do you want to call them? What is pleasant to you? Reading a book or watching TV?

Have you been crying? My poor friend is in terrible state.

Why don't you try to get some sleep and maybe you can call them tomorrow.

Have you been crying? I should be punished. I should be dead.

You are only human. Do you want to talk to someone? Maybe your family or the psychiatrist?

Have you been crying? Sad movies tear my heart out.

Do you want to talk to someone so that you can feel better?

Have you been crying? I don't deserve to be alive!

Do you want to talk to someone? Maybe your family or the psychiatrist?

Have you been crying? I don't know what is happening to me.

Do you want to try to write down your thoughts? Do you want to talk to someone?

You haven't been moving your body a lot recently. Is there something wrong? My legs are killing me!

Do you want to try small exercises or a massage. If it hurts too much you can take a painkiller.

You haven't been moving your body a lot recently. Is there something wrong? The room is spinning.

Do you want to sit down for a bit? Maybe you can measure your blood pressure or eat something.

You haven't been moving your body a lot recently. Is there something wrong? I can't keep my eyes open.

Maybe it is better if you took a small walk or if you talked to someone.

You haven't been moving your body a lot recently. Is there something wrong? I cannot bring myself to do anything.

Maybe it is better if you took a small walk or if you talked to someone. Do you like music?

You haven't been moving your body a lot recently. Is there something wrong? I can't get any sleep.

Maybe it is better if you took a small walk or if you talked to someone. Do you like TV?

You haven't been moving your body a lot recently. Is there something wrong? There is nothing to do.

Maybe you can go for a walk or you can start a new hobby or talk to someone.

I noticed you haven't met with someone or even talked to someone these last days. I don't want to see anyone.

Maybe you can go for a walk or you can start a new hobby or talk to someone about it.

I noticed you haven't met with someone or even talked to someone these last days. I am alone in this world.

You can always talk to someone or you can go to the church.

I noticed you haven't met with someone or even talked to someone these last days. I wish I had the time.

Do you want to organize your schedule from the previous day or invite your friends when you go out?

I noticed you haven't met with someone or even talked to someone these last days. I am broke and cannot do anything.

Are there any free activities that you can share with your friends? Can a friend come to your house?

I noticed your blood pressure is increased lately. Are you felling ok? Nothing can make me relax.

Do you want to sit on the balcony for a while or listen to some music?

I noticed your blood pressure is increased lately. Are you felling ok? My head is killing me.

Do you want to take a painkiller? It is better if you avoided coffe or alcohol.

I noticed your blood pressure is increased lately. Are you felling ok? I don't want any more pills.

Your family knows that you take your pills regularly. Do you want to talk to your doctor?

I noticed your blood pressure is increased lately. Are you felling ok? I can't sleep even for one second.

It is better if you can reduce alchol, coffe or smoking. If you want to, you can talk to your doctor.

I noticed your blood pressure is increased lately. Are you felling ok? They keep changing my drugs.

It is for your own good.Do you want to talk to your doctor for possible side-effects?



6.4 Instrumental Power-Instrumental Power Complaint-Recommendation Interactions

I noticed you have insomnia. Did you experience difficulty sleeping? I was nervous ok?
It is already late and you will be exhausted, go to bed even if you don't feel like it.
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.
Why do you eat or drink before bed? Don't you care about yourself?
I noticed you have insomnia. What did you do wrong and you can't sleep well? I am never drinking water again at night.
Then you have to stop drinking water before bed immediately.
I noticed you have insomnia. Is there a reason why you didn't sleep well? My exercise is keeping me from sleeping, I am quitting.
It is very clear. Never exercise before bed or you will have difficulty sleeping.
I noticed you have insomnia. Is there a reason why you didn't sleep well? I am going to fall into depression.
It is important to think positive before bed otherwise you will have a problem sleeping.
I noticed you have insomnia. Is there a reason why you didn't sleep well? I will never call my friends again.
It is your responsibility to keep a steady routine before going to bed.
I noticed you have insomnia. Is there a reason why you didn't sleep well? TV makes me want to jump off a cliff.
You should choose wisely the TV programs you watch or you will experience insomnia.
I noticed you have insomnia. Is there a reason why you can't sleep? I am going to faint from the heat.
If you want the symptoms to stop, you should lower the room temperature immediately.
I noticed you have insomnia. Is there a reason why you can't sleep? I will faint from this pain. If you don't want to hurt, you must take a painkiller.
I noticed you have insomnia. Have you started a new drug recently? I will quit this new bloody pill.
You cannot stop this pill before you talk to your doctor.
Have you been crying? I am getting depressed.
If you do not take the initiative to take a walk or talk to someone, your mood will not change.
Have you been crying? Did you see what happened to him? I am getting depressed. If you call them now, you will be more stressed. You can call them tomorrow.
Have you been crying? Why should I stop crying?
Didn't you think of new drugs the doctor prescribed first?
Have you been crying? I feel guilty. It's my fault. If you make your own conclusions and don't talk to the psychiatrist, you will not solve this problem.
Have you been crying? I am going to fall into depression because of that movie.
If you will not talk to someone, you will feel bad for no reason.
Have you been crying? I want to hurt myself. I hate myself. I want to die. This is the time to talk to a psychiatrist.
Have you been crying? I don't know why I want to hurt myself.
If you will not talk to a friend or a psychiatrist, your mood cannot change.
You haven't been moving your body a lot recently. Is there something wrong? I feel so much pain I am going to tear up my clothes.
The correct solution is to take a painkiller or call your doctor.
You haven't been moving your body a lot recently. Is there something wrong? I feel dizziness and want to hit my head against the wall.
If you do not eat properly and you make sudden movements, what do you expect?
You haven't been moving your body a lot recently. Is there something wrong? I feel tired and do not want to do anything.
If you do not take initiative to change your life and go out for a walk or have a hobby, you will not feel better.
You haven't been moving your body a lot recently. Is there something wrong? I am not in a good mood and do not want to do anything.
It is time to get out of the house and walk.
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 and do not want to do anything.
It is time that you started a new hobby.
I noticed you haven't met with someone or even talked to someone these last days. I am not in a good mood to do anything.
It is time to start communicating with more people by going out or talking to someone.
I noticed you haven't met with someone or even talked to someone these last days. I don't have friends and I will never have friends.
If you don't take the initiative to call your friends or to meet them, nothing will change in your life.
I noticed you haven't met with someone or even talked to someone these last days. I don't have time and I chose my program.
It is clear that you should take out some activities from your program so that you will meet your friends more.
I noticed you haven't met with someone or even talked to someone these last days. I save money and I don't want to spend it on useless things.
If you really want it, you can always find free activities to do with your friends.
I noticed your blood pressure is increased lately. Are you feeling ok? I feel sad. I feel nervous and too stiff to relax.
If you really want to relax, sit on the balcony or listen to music.
I noticed your blood pressure is increased lately. Are you feeling ok? I feel pain. I'm in pain and I want to smash you with my bloody machine.
If you feel pain and you are so uncomfortable, the solution is to call your doctor.
I noticed your blood pressure is increased lately. Are you feeling ok? I didn't take my pills and I won't.
Call your doctor and do not jeopardize your health.
I noticed your blood pressure is increased lately. Are you feeling ok? I will stop those bloody new drugs. Take your pills as soon as you remember it and do not jeopardize your health.