Ideas for the Web-Based Affective Processing

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ABSTRACT

As most of us subconsciously feel, it is a great difficulty to create a program which could imitate human's way of thinking. Recently the importance of the relation between expressions "feel", "create" and "way of thinking" used in the previous sentence is being noticed, what gave birth to so called "affective computing". During our experiments within GENTA project, we have observed useful connotations between the common sense information and the emotional information which could be retrieved automatically from the Internet resources. Those observations seem promising for the language and knowledge acquisition and suggested us to investigate the subject, and also to develop some ideas, which could be useful to the researchers in various AI fields. We describe GENTA-related sub-projects and their preliminary experiments.

Keywords: Affective Computing, Common Sense, Average Personality Creation.

1 INTRODUCTION

The most popular objection against the possibility of creating an Artificial Intelligence is that the machines will never be able to be like human, as they can operate only on "0" and "1" level. Everything for the computer is black or white, true or false. Even the fuzzy logic with its infinite results sounds "artificial" and for most observers it will be the "pure mathematics" far from humans' way of thinking, feeling or creating. During the last decade many scientists have underlined the meaning of emotions [1, 2, 3, 4] but still the AI is said never to feel anything. We claim that machines do not need feelings for themselves but they must understand human's emotions. By making them understand that some of their actions could injure, insult or harm its user, we would be able to provide a safety valve, which surely will be demanded when the machine learning and robot's supposition abilities become usable in everyday life. If we imagine a housework robot which recognizes an unknown object on the kitchen table as an apple, we would not want our robot to trash it, even if the priorities say "keep the kitchen table clean". First of all, the robot should have a commonsensical knowledge about the recognized object. Albeit the situation takes place in 10 or 20 years when the recognition level is almost perfect, "an apple" would be still only a meaningless noun, which could be later consulted with a user. But there are objects and situations that should be considered for example as dangerous and the need of immediate action appears, as a knife on the table and a child around. In such cases the lack of common knowledge toward the newly recognized object can end tragically. Secondly, our robot should know what kind of emotional reaction of the user will his action cause. Getting rid of a rotten apple would probably be a good thing but trashing a fresh one would not make the user happy. How to make the robot achieve the lacking knowledge at spot? Do we have to enter every situation, combination of situations, all cases, all conditions? Must be affective computing based on complicated logic formulas? Our idea is to use the knowledge hidden in the billions of homepages, which are born and die like living organisms. Our hypothesis is that the numbers of experiences and the feelings accompanying them are creating our personalities and influence our actions and our goals. As it would be probably impossible to enter all experiences, opinions or utterances heard by a single person, we decided to always retrieve an average knowledge about the matter, which could help us to build an average personality with what usually call a "common sense". Most of researches avoid using the Internet as a database since most of homepages contain data seeming useless for business purposes and their contents in most cases resemble each other as in blogs where people describe their ordinary life. But for our idea this big number of similar data is the most important part. One big event of our life is able to change our future but it will not give us the commonsensical knowledge. We achieve the common sense by experiencing repetitions of small events and remembering them best when stimulated emotionally.

2 AFFECTIVE LOGIC

As we mentioned above, machines do not need emotions and probably they should never have feelings for the ethical reasons but it is necessary for them to understand the emotional reactions of their users. However, describing our reasoning with classical logic was never easy as there are too many conditions influencing every single decision we make. Even seemingly unimportant background experiences influence most of our acts. Formal logic is formal literally and if we exchange 0 with "wrong" and 1 with "correct", or getting deeper into the emotional sphere, "bad" and "good", we will easily see that classic rules will not work for everyone, since everyone has different personality built on different experiences. What seems good to a child seeing a cake and the lollipop:

positive + positive = positive (1 + 1 = 1)

could be seen differently by its parent who recognizes sweets as a danger for the child's health:

positive + positive = negative (1 + 1 = 0).

If the person does not like sweets, the negative elements could give a positive sum as there is an advantage of not getting too much sugar (0 + 0 = 1) and at the same time smoking and drinking can give opposite associations (1 + 1 = 0). As we can see in these examples, it is difficult to understand somebody else's point of view without deciding what is good for who. However, every one of us has a mechanism which is being developed through the whole life - the common sense. This is the commonsensical knowledge that decides what is usually good or bad for who and in which cases – with the stress on our opinions build on our experiences. We presuppose that the initial common sense bases strictly on feelings coming from the physical perception and then develops mostly on the environmental perception by which we mean a learning from the third parties' experiences. Let us get back to the example with sweets. When we are very young, we prefer decisions based on our own perception and if the sweets taste good, we are not willing to stop eating it if somebody on TV says that it is bad for our health. But it again depends on who and how is talking about the matter. If the child is tied emotionally to the persuading person or a character, the effect is usually stronger. Or if we stimulate child's imagination by for example creating a vision of bad little creatures eating the teeth, the teaching process seems more effective. Consequently we could make a machine simulate human basic instincts and gain experiences the way we do. But we think it is not needed if the machine could retrieve the already achieved results of such learning. We seek such results in the Web. The "affective logic" still does not have firm rules and it is under development. We would rather make the machine find this logic than to enforce stiff frames. The basic ideas that are to be implemented will be more understandable with actual usage examples.

3 GENTA PROJECT

Our project called GENTA (GENeral belief reTrieving Agent) is basically being developed in three directions. As the furthest goal we chose the freely talking agent (or robot in the future), which could correctly response to the emotional information included in the user's utterances or behaviors. The second issue we engaged ourselves in is the Bacterium Lingualis method for retrieving the commonsensical knowledge. The last part of our project are preliminary experiments toward implementing two first parts into a robot, since they are difficult to be evaluated on the theoretical basis.

3.1 Dialog Agent

In this part of our project, we are trying to realize a con-

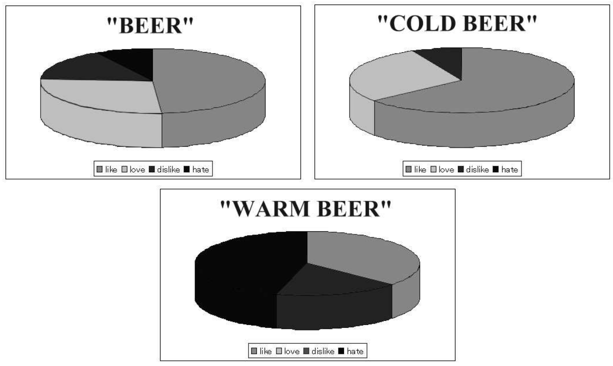

Figure 1. Positiveness ratio comparison for expressions "beer", "cold beer" and "warm beer"; the darker the Positiveness value is lower.

versational agent, which would be able to talk in any domain by using web-mining techniques to retrieve information that is impossible to obtain in usually used corpora. We try to simulate reasoning processes based on Internet textual resources including chat logs. As we mentioned before, our main goal is a dialog system which learns the linguistic behavior of an interlocutor concentrating on the role of emotion during analyzing discourse. The system is not using any databases of commonsensical word descriptions, they are being automatically retrieved from the WWW. The basic philosophy of our approach is noticeable in two values called Positiveness and Usualness . A simple mechanism calculates Positiveness value retrieved from the Internet users' opinions:

$$Positiveness = \frac{C_{\alpha_1} + C_{\alpha_2} * \gamma}{C_{\beta_1} + C_{\beta_2} * \gamma}$$

$$\alpha_1 = disliked, \alpha_2 = hated$$

$$\beta_1 = liked, \beta_2 = loved, \gamma = 1.3$$

Where γ is to strengthen the "love" and "hate" opinions. This method helps the system to recognize if an object is

- **very positive** (Positveness = 5)
- **positive** (Positveness = 4)
- **indifferent** (neutral) (Positveness = 3)
- **negative** (Positveness = 2)
- **very negative** (Positveness = 1).

and to provide the common information about what humans feel toward the given object.

The "Usuallness" value is based on Shannon's information theory [5] and symbolizes the frequency of an expression. We assume that the lower Usualness is, the more interesting the expression is for the interlocutor. These two values help the agent to guess the General Belief. By this expression we mean a mixture of common sense and average opinions retrieved from the Internet. The system works and learns from the textual IRC chats. Before starting a conversation, the knowledge about a user is assumed as almost none – GENTA does not know the nationality, age or sex of its conversation partner; he or she is not necessarily a native speaker of English. After exchanging greetings, the system waits for a user's initial utterance and if there is none it starts a conversation using the learned data of "Conversation Keeper", which is described with more details in our previous works[6].While detecting the speech act, GENTA tries to guess the leading keyword(s) from the first user's utterance since the domain of conversation is still unknown. Next, GENTA searches the Internet for the whole utterance and its grammatically connected parts previously parsed by a parser[7] trying to establish what can be associated with given verbs, nouns, noun phrases, adjectives or conditional expressions concentrating on feelings-based opinions. This lets our system achieve "own" opinion about the spoken matter because this knowledge is assumed as "general" or "common". What is characteristic for our method, even if the Positiveness of expression seems to be doubtful (for instance it appeared that the most Web page creators like it when it rains that does not necessarily mean that most human beings also do) it does not disturb the process since the opinion remains logical. Next, again paraphrasing Shannon's theory[5], we assume that the keyword with less frequency is more interesting for interlocutors and GENTA chooses leading topic according to the Usualness. The system believes that the discourse should be continued in this "semantic direction". But before that, "Conversation Keeper" must establish which linguistic behavior (called "a dialog act" here) will be proper for a reply, which was the first task for our agent. We made an experiment where the agent was calculating the Positiveness value of one interlocutor and then guessing what kind of emotional load would the response include. The inductively learning system started to use learned rules already by the eighth turn, as the chat was mostly question-answer style, but finally less than half (37.5%) of dialogue acts were chosen the same way by a user. Although 81.25% of those different ones were evaluated afterwards as natural by human being. More details can be found in other publications[6, 8] therefore we will concentrate on the remaining parts of our project.

3.2 Bacterium Lingualis

Numerous thinkers of our times discuss the possibility of creating a machine which could be a conversational partner on an equal level with humans. One of the main problems is the fact that we do not really know how our mind works and how it produces a language. Without this knowledge, developing an algorithm which universally simulates humans' linguistic behavior is extremely laborious if not impossible at all. The challenge of improving learning abilities for so called "intelligent machines" is very tempting for many researchers but by observing language and knowledge engineering for last decades we noticed a tend for complicating and deepening of computational analysis, which accompanies the technological advance, while the effects of the learning algorithms seem not to be satisfying. Although many bottom-up methods were developed, their learning abilities are still relatively poor as they lack an universality. Hence we started working on the idea of "Bacterium Lingualis" method of inter-domain knowledge acquisition based on Internet text resources and affective computing.

3.2.1 The Concept

As Penrose [9] claims, the intelligence may be a fruit of our development based on Darwinian natural selection. The ideas of how to catch an animal into a trap were developed long time before a human started describing things in an abstractive manner as in logic or mathematics. Many of the artificial intelligence researchers agree that bottom-up simplified learning methods are the key to broaden the computer's capabilities and various algorithms were developed so far. The most popular ones are inspired biologically, as for example Artificial Neural Networks, genetic algorithms or insect colonies. Their weaknesses differ from one to another but they are not independent and they need laborious trainings. "Bacterium Lingualis" has a lot in common with the methods mentioned above but its differences come from the new possibilities brought by the Internet development. When we realized that pure logic is not enough for the machines to be rational and that they need all background knowledge that we have [10], it was time to start teaching computers the commonsensical knowledge. Unfortunately it seems to be a Sisyphean task and even projects as CyC [11] or global OpenMind [12] are far away from being successful. We claim that full automatizing of this task is necessary and we should use as big corpora as possible, since, as we mentioned in the Introduction, not only the quality, but also the number of commonsensical inputs is crucial for learning the laws ruling our world. We "stepped back" in evolution and started creating an insect to start learning from the very bottom without forcing it to behave on Cartesian philosophy. By Latin "Bacterium Lingualis" (hereafter abbreviated as BL) we mean a kind of web crawler which exploits only the textual level of WWW resources and treats it as its natural environment. We assume that cognition, by which we mean the process or result of recognizing, interpreting, judging, and reasoning, is possible without inputs other than word-level ones - as haptic or visual [13, 14]. Although such data could significantly support our method, a robot which is able to travel from one place to another in order to touch or smell something, would cost enormous amount of money, not mention a fact that current sensors technology is not ready for such an undertaking. There are several goals we want to achieve with BL, which is an "engine" of the GENTA project. The main one is to make it search for the learning examples and learn from them unsupervisedly. For that reason we decided to move back in evolution and initiate self-developing BL on the simplest level with as few human factors as possible. We assumed that all human behaviors are driven by one global reason - the pursuit of good feeling which seemed to us more adequate than simple natural selection. On the basis of above mentioned assumption we formulated "good feeling hypothesis" (hereafter abbreviated as GFH) and we implemented BL with simple negative and positive factors recognition mechanism mentioned in the Dialog Agent section. GFH determines the motivation for knowledge acquisition which involves language acquisition as the living environment for our program is language itself. We imagine a language as a space where its components live together in a symbiosis. Its internal correlations

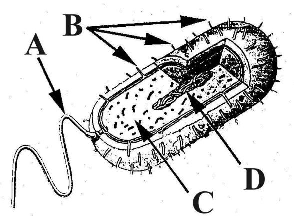

Figure 2. Bacterium Lingualis (A - Flagellum, B - Positiveness Receptors, C - Concrete and Abstract Knowledge Memory, D - GF Cell)

are not understandable for BL and the learning task is to discover them. For exploring such an area we use simple web-mining methods inspired on Heylighen et al.'s work [15]. Most of the researches suggest that a machines have to be intelligent to mine knowledge for us, we suggest that they have to mine for themselves to be intelligent.

3.2.2 Bacterium's Structure

In order to make their idea clearer, and not to confuse their system with agents working for users, the authors decided to use a concept of an imaginary bacterium, although the rules of the language world (called here Lingua Environment) and its rules should not be considered as strictly corresponding to the biological world in which we live. BL's organism is capable of moving if the relocation is needed, to sense food and enemies, excreting what is useless. We also equipped it with enzymes and two kinds of memory, which will be detailed hereunder.

3.2.3 Lingua Environment and Enzymes

We created the BL's environment according to ideas proposed earlier [6]. To achieve better uniformity we decided to replace English language homepages used in the beginning with Japanese homepages since this language seems to have an easier structure for processing especially because its particles usage what Fillmore has suggested in his papers [16]. The particles behave like enzymes connecting objects (e.g. nouns) with other objects (e.g. verbs) on the semantic level —$Sapporo$—de—(live, saw, take place...)
—$Sapporo$—ni—(go, come, arrive...)
—$Sapporo$—to—(Nagoya, compare, Otaru)
(...known, related, belonging)—u—$Sapporo$—
(...nice, nostalgic)—i—$Sapporo$—
(...strange, wonderful)—na—$Sapporo$—
Since the causal relationships are crucial for the reasoning, several "IF enzymes" were prepared to be combined with discovered neighbors. It was relatively easy because nouns, verbs and adjectives have the same elastic if-forms in the Japanese language: *konpyuutaa-dattara* (if computer)
tsukattara (if to use)
aokattara (if blue), etc.
For experiments we have collected almost three millions .jp domain homepages with the Larbin robot , then after filtering off pages without sentences in Japanese and converting them into pure text files, we created a web-based raw corpus consisting of about 2.090.000 documents (approx. 20 Gb). No tagging or whatsoever was conducted.

3.2.4 Flagellum

Flagellum symbolizes BL's ability of movement inside its environment by which we mean text mining techniques. For these purposes we used Namazu indexing and searching system which has ability to separate words with spaces in so called wachigaki mode as Japanese sentences do not contain spaces. This helps BL to recognize what elements the contacted organism (by which we mean semantic units as text, sentence, words cluster, etc.) consists of. The morphological analysis could be done by recognizing similar patterns and statistical calculations but we assumed that omitting this level would not harm the results of BL's performance and will shorten the processing time.

3.2.5 Positiveness Receptors

As we mentioned before, BL is able to automatically determine its emotional reaction to the observed object. It is done with Positiveness value calculation described in the Dialog Agent section. For instance, if the BL contacts with a single noun "beer" its reaction is positive (Fig. 1), when the "organism" consists of two elements: "cold" and "beer", receptors send a P5 signal (very positive, Fig. 1) to the GF cell, which will be described further. In the case of an unusual organism as a combination of "warm" and "beer", BL receives the negative signal (Fig. 1).

3.2.6 Concrete and Abstract Knowledge Memory (C)

BL is able to store gained knowledge. Its memory is divided into two coexisting units, Concrete Knowledge Memory and Abstract Knowledge Memory. Both are equally important but only the growth of the latter we consider as the system's growth. At this point of the system's development the concrete knowledge stands only for retrieved chains database, the abstract one describes a dictionary of automatically categorized groups of objects that frequently appear in similar combinations. This will be explained in the Method section.

3.2.7 GF Cell (D) and the Good Feeling Hypothesis

As we mentioned above, the logicalness of human behavior is often very difficult to be analyzed with mathematic approaches. We assumed that natural language itself should decide the rules for BL system, however, it must have some inborn initial instincts as its biological equivalent. Our Good Feeling Hypothesis is supposed to realize this task. We presuppose that if any activity of a human has been always motivated by pursuing desire of "good feeling" also the language was one of the tools for achieving this goal and is based on the same "affective logic". Therefore, "Good Feeling Hypothesis" assumes that implementing such a mechanism to a machine could help it to acquire knowledge and language. Following our thought that the GFH or defense of GFH are the reasons of every behavior, we inputed this two simple rules into GF Cell and made it default final conclusion of any reasoning while searching for different "sub-reasons" on its way.

3.2.8 Basic Method

As we want to start our experiments on the lowest level of language mechanisms, the first experiments we conducted were to achieve automatic responses resembling Pavlovian reactions in the biological world. Such responses are needed to identify the object as pleasant, unpleasant or neutral and provoke a system's suitable behavior, by which we mean the ability of reasoning on the emotional ground. On this stage, the BL uses only a very simple algorithm mostly for the associations gathering and reasons lookup. The basic part works as follow. First, it measures the Positiveness value of a contacted object. In the beginning, it has no syntactic knowledge but while measuring the Positiveness it is able to recognize if it is analyzing a verb, a noun, an adverb or a particle etc., since the "enzymes" link only specific objects.

For example a Japanese particle *DE* (at) does not appear after a verb. Although we prefer words grouping by their connections with particles, what bases the categorization on more metaphoric grounds, for the time being we limited input only to the nouns. If, for instance, "Sapporo" was inputted, BL seeks for the most frequent input-particle strings to decide three most suitable enzymes. In the case of "Sapporo" they are *NI* (to) (approx. 94.000 hits), *DE* (approx. 80.000 hits) and *KARA* (from)(41.700). For better accuracy this is done by Perl API for Google . The object "Sapporo" is recorded in Concrete Knowledge Memory in the NI-DE-KARA category, which is characteristic for places. Then, the mining process starts and the neighbors of Sapporo-ni, Sapporo-de and Sapporo-kara are found. Also in this case we limit the search only to the three most frequent neighbors. The candidates are taken from the first ten results and again the frequency for them is measured. Then, the next neighbor is searched. The process is being repeated until the last possible neighbors found. After that, the string is saved in the Concrete Knowledge Memory. If there are other objects remembered in the same category, the inputted one is replaced with every one of them:
$Object_1$—enzyme—$string_1$—$string_2$—$string_n$
$Object_n$—enzyme—$string_1$—$string_2$—$string_n$
If one of them exists in the Lingua Environment, the abstract string is being saved at the Abstract Knowledge Memory:
$Sapporo1$—enzyme—$string_1$—$string_2$—$string_n$
$Object_n$—enzyme—$string_1$—$string_2$—$string_n$
creates an abstract chain:
$NI-DE-KARA$—enzyme—$string_1$—$string_2$—$string_n$
We suppose that that collecting such abstractive rules based on the common sense may be very helpful also as a support to the other systems. The idea of using common parts in expressions to make abstractive rules is influenced by Araki et al.'s Inductive Learning [17]. If the analyzed neighbor object does not exist in the Concrete or Abstract Knowledge Memory, BL checks if it is processable with enzymes, that is if it appears with particles which determines of it is an individual object. If not, the object is deleted.

3.2.9 Experiment and its Results

For the first test of BL method, we made it search for the connotations explaining why the object being analyzed are regarded positive or negative. A group of 10 students assigned Positiveness value for 90 words picked by BL system as those which have distinct bad or good associations. We have confirmed that 36.3% of selected words were evaluated by humans as neutral, without any emotional connotations. For proving that objects' emotional load varies from a situation, we made BL find a reasonable chain of conditions for 5 words that seemed to be indifferent for most subjects. No word was recognized as neutral by every subject, what proves that associations of one expression are sometimes positive and other times negative depending on individual connotations. Discovering the examples of conditions or situations for both positive and negative associations was the task for the experiment. Differently from the methods proposed by Heylighen et al., BL does not only count the co-occurrences but actually mines further the inputted noun's neighbors and measures its Positiveness also if it is a verb or adjective. This done by a "'$noga$ enzyme", which consists of two particles making verbs and adjectives behave like nouns: *(V/Adj)-no-ga*. Using the same method and "$noga$ enzyme", BL is able to determine that *eiga-o mi-ni iku* (to go to the movies) or *yasashii* (kind) are commonly positive and *uso-o tsuku* (to lie) or *mendoukusai* (troublesome) are distinctly negative. The words that were recognized as neutral were: *fun'iki* (mood), *dashi* (*dashi* soup), *jouken* (condition), *seikaku* (character) and *kumiawase* (combination). Here is an example of the correctly retrieved reason:
"mood / atmosphere" ($fun'iki$)
positive:
chiisai—snakku—no—ochitsuita—$fun'iki$
(calm atmophere of a little bar)
negative:
shiai—no—mae—piri-piri-shita—$fun'iki$
(irritation before a game)
and an erroneous one:
"combination / set" ($kumiawase$)
positive:
ninniku—nigate—futari—$kumiawase$
(set of two persons who can't eat garlic)
negative:
???—shujinkou—to—hiroin—$kumiawase$
(reason not found - combination of hero and heroine)

We can see that the BL could not find the reason what kind of hero and heroine could be a bad combination but it is possible to make BL search for Internet's most disliked couple and try to fill in the blank. Such kind of "imagination" is also part of our interests, even if its creative abilities would not be very original. However knowing what is average can help detecting what is original. Output achieved during the experiment is not ready to be used by language generation programs but we presuppose it could be used in common-sense based talking agent mentioned in Dialog Agent section or for implementing it into a robot mentioned below.

3.3 Housework Robot

The third and the youngest part of GENTA project is an Common Sense Engine for a housework robot we are building upon the Open Pino Platform. Since the affective computing is difficult to evaluate we decided to implement our ideas into a machine which will be demanded by the society in the future. The preliminary simulations showed that Pino is able to guess what action it should choose and what tools it should use. What seems interesting, it is able to choose not only basic items currently available but also it asks for products like "magic sponge" as General Belief of Internet users is recommending it.

4 CONCLUSIONS

It may seem difficult to undertake such a big, three level project but we believe that only the full collaboration of discourse processing, web-mining techniques and the real-life supporting machine can give us desired effects and prove the usability for affective processing. Obviously a "good feeling" varies according to the individual features but we discovered that some standards can be retrieved. Since we aim at creating unsupervised system, these standards are also supposed to play the role of safety valve. This is possible because the idea of Positiveness is based on average opinions of the homepages creators. It prevents the system from remembering chains like "killing is good" as the commonsensical facts. Another purpose is to get rid of nonsensical outputs of learning or mistaken strings that are created during the processing. We still can not demonstrate the satisfying results but since this is still the early stage of GENTA development, we hope to provoke a discussion as well as to inspire other researches interested in affective computing.

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