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Forgetful and Emotional: Recent Progress in Development of Dynamic Memory Management System for Conversational Agents

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Abstract. Thinking of the ways to improve naturalness and adequacy of utterances in conversational agents, the authors propose a dynamic database management system. The system borrows some features of the forgetting mechanisms in humans. The core of the system, forgetting and recalling algorithms, depend on the frequency of usage of context units and their emotive values derived from evaluative reasoning about both sides of interaction - the agent and the user.

1 INTRODUCTION

Forgetting is a process in which parts of knowledge become rearranged, inaccessible or inactive [1, 2]. In neuromedical terms, forgetting is a result of the fact that as living and growing old beings, we cannot keep the neural connection net of our memory in a perfect shape forever. Every new neural connections made in our brain start decaying right after being settled [3].

The research about chronological fading of memories was started by Ebbinghaus [4] in an experiment with remembering series of syllables, which revealed that fading of memories is inversely proportional to the time expired.

Zitman [5] discovered, during his observations of patients with mood and anxiety disorders, that memory has much in common with emotions, which he confirmed in experiments on hormonal transfers. Nuray Luk [6] supported similar thesis in her research on the role of emotions in language acquisition. Wolfe [7], although using neurobiological nomenclature, stated similarly, that the brain at first seeks to create meaning through the establishment or refinement of existing neural networks (or actualization of the database of our memory) and further, during the process of learning affects it with emotions. Therefore memories with stronger emotive affection are harder to forget.

People usually find the forgetting process a disadvantage or a defect in the human mind. However, as the research on human brain continues, more features of our way of thinking undergo reevaluation. When Markovitch and Scott [2], stated that forgetting *"is a very useful process which facilitates effective knowledge acquisition"*, and that *"mechanisms of forgetting (...) merit study alongside those of acquisition since it is the two together which constitute learning"*, they tried to give forgetting a logical reasoning. However, it's the results of the experiments performed by Kahn et al. [8] that show that forgetting not only is not a defect, but on the contrary, actually helps people organize memory and remember important things.

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Therefore, to improve naturalness and adequacy of utterances in conversational agents, the process of forgetting could be applied as well. We propose its application in the form of a system for dynamic management of the agent's expanding database resources. The idea of such a system is based on the following assumptions:

- Memory is an expanding database;
- Forgetting is a crucial element in the process of learning, and
- is beneficial in organizing knowledge;
- Forgetting process is strongly dependent on:
  a) frequency of connections in use, and
  b) emotional value of connections

As we assume, final implementation of such system should help process large text databases for conversational agents and effect in two major improvements: cutting down the time costs of wide context processing and allowing the agent to produce more natural utterances.

2 SYSTEM DESCRIPTION

In a conversational agent supported with an expanding database (DB, see Figure 1) all interactions with the user are archived (the archivization can be set as user-specific for better calibration of personalization algorithms). When a user encounters the agent, a new conversation starts. After every user input the agent queries the database searching for adequate context keywords (n-grams, conversational procedures) to produce an utterance. If there are none the agent queries the Internet for adequate associations. Every entry after a query is treated as a separate Context Unit (CU). For better distinction the context units are divided into Context Units obtained from a dialog with a user (dCU) and those in the form of an association lists gathered from the Internet (aCU).

However, since the database expands with every new CU, soon the agent would have to process enormous number of data. As is stated Araki [9], this is one of the difficult problems in processing context-bound sentences. To avoid this authors propose a system with an implemented algorithm of forgetting and recalling of the data archived in CUs according to the actual needs.

2.1 Forgetting algorithm

As stated above, forgetting is a process where parts of knowledge become inaccessible or inactive, which in humans contributes to better management of memory. Since there are context connections in the DB used more often and those used rarely, it is reasonable to base

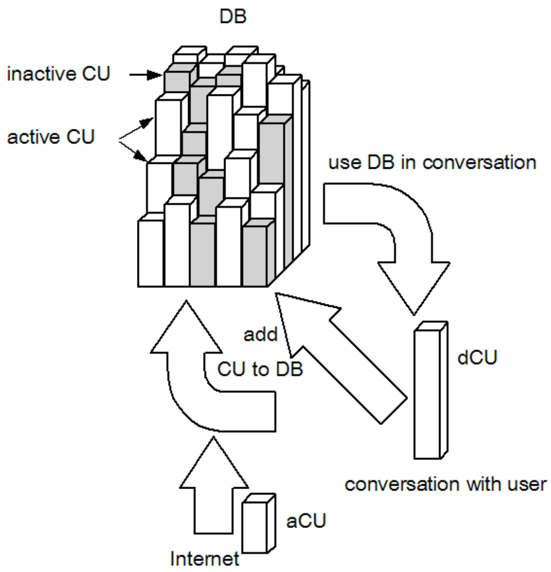

Figure 1. Generalized diagram of the system.

the forgetting process on the frequency of use of the connections. That is, if a connection is not used for a specified amount of time, an event would be marked as inaccessible. Moreover, forgetting in humans is based also on the emotive strength of neuronal connections, which could be represented by using an affect analysis system to add annotations of emotions to the archived CUs during the process of gathering information.

The contents to be forgotten by the agent are selected and the final decision whether to shade a CU is based on the values representing the two features:

1. frequency of CU usage, and
2. emotional strength of CU.

2.2 Recalling algorithm

Although there have been attempts of creating an algorithm of forgetting before with some good ideas, it seems that the attention was always concentrated only on forgetting during the process of learning. Markovitch and Scott [2], as well as later Ishikawa [10], by forgetting meant that the unused links of a large amount of knowledge are forgotten by the means of physically deleting them from the database. Unfortunately, this way the notion of recalling information from the faded database was ignored.

In the proposed algorithm the recalling process works simultaneously with the process of gaining new knowledge (CUs). When the user talks to the agent, a new conversation starts and the agent searches through its database for an appropriate context data to generate a response. If a match is established and the response generated, the connection to the used context is renewed. If not, the agent skips to the process of gaining knowledge from the Internet. When a new associative context unit (aCU) is obtained, it is compared to the inactive forgotten archives. If the new gained aCU associates with an inactive (forgotten) parts of knowledge in the database (dCU), those parts are activated and their connections renewed. If the aCU contains only new data and does not associate with any other CU, it is added and archived in the database as a new active CU.

3 CONDITIONS FOR IMPLEMENTATION

In the usual indexing methods for textual databases [11, 12], the process of indexing and reevaluation of indexes is usually based on chronology of the established link and the frequency of its reappearance in queries. In the proposed method, apart from this type of indexing, the data is indexed also with information about its emotional value. As there are at least two participants of interaction - the user and the agent, to set such a value there was a need to develop two algorithms for evaluative reasoning about: 1) the user and 2) the agent.

3.1 Evaluative reasoning about user

The algorithm for evaluative reasoning about the user, is based on the assumption that the user can produce either appropriate or inappropriate utterance. To evaluate what is appropriate we based this algorithm on Ptaszynski et al's [13] method for verification of contextual appropriateness of emotions. In their method they used a system for affect analysis ML-Ask to recognize user's emotions and a Web mining technique as an emotion appropriateness verifier (both described in details below).

When ML-Ask discovers an emotive utterance and successfully specifies an emotion type, the Web mining technique extracts emotions frequently associated with the context of the utterance. The verification is based on the comparison of the emotions discovered by ML-Ask in user's utterance and the Web mining procedure results.

If the two match, the emotions expressed by the user are determined as appropriate. In such situations, the conversational agent equipped with this method chooses a dialog strategy to sympathize with the user. However, if the verification procedure estimates that the expressed emotions are inappropriate for the context, the agent undertake different measures e.g., helps the user manage his/her emotions. Four examples of the output of this method are shown below in Table 1.

The conversations with the agent are archived in the database with annotations of both features - emotions expressed by the user and their appropriateness. Primarily, this data is used in future interactions to provide the agent hints about which conversation strategy to choose, according to the appropriateness of the user emotions [13]. In the database management system the annotations of those two features on one whole context unit (CU) form fluctuations of the two features in the particular CU. The number of emotive utterances and emotional state fluctuations is further used as the first part of information used by the forgetting-recalling algorithm - evaluative reasoning about the user.

Table 1. Four examples of the appropriateness verification procedure.

Sentence (Translation)	ML-Ask output	Web-mining [appropriateness]
Shiken ni goukaku shite ureshii! (I'm so happy I passed the exam!)	joyful	joy, happiness [appropriate]
Ano yaro ga kuruma ni hikarete, sukkiri! (Im so happy that bastard was hit by a car!)	joyful	fear, sad [inappropriate]
Kanojo ni furarete kanashii... (Im so depressed since my girlfriend left...)	sad, depressed	sadness, gloom [appropriate]
Iisutaa ga kuru kara kanashii ne... (Im so depressed for the coming Easter...)	sad, depressed	joy, happiness [inappropriate]

3.2 Evaluative reasoning about agent

The information obtained from the affect analysis system ML-Ask is also used to estimate the user's attitude to the agent and therefore to perform evaluative reasoning about the agent.

The results of affect analysis of each utterance provide information on how many user utterances were emotive. Furthermore, the emotions extracted from the user's emotive utterances form a vector on which the emotional states of the user changed during the conversation. This information is then processed as follows (described in detail by Ptaszynski in [14]).

Firstly, if numerous user's utterances were determined as emotive, we assume the user was emotionally involved in the conversation. Emotional involvement in a conversation suggests a tendency toward easier familiarization with the interlocutor [15]. Therefore we can assume that during the user's conversation with an agent, the machine interlocutor is considered to be more human-like the more emotionally emphasized the user's utterances are.

However, this does not yet mean a positive familiarization. The conversation could become emotional also when the interlocutors quarrel. This could happen in a case where the agent makes the user angry. However, if the user agrees to participate in a quarrel with an agent, this could also mean that the user finds the agent's linguistic capabilities to be comparable to himself. Therefore, the information obtained about the general emotional level of the conversation could be interpreted as signifying how much the user finds the agent worth talking to, including familiarity and the user's opinion about the agent's linguistic skills.

Secondly, analysis of specified emotion types conveyed by the user in the whole conversation provides information on the user's particular emotions during the conversation. If the emotions were positive or changing from negative to positive while talking, the general attitude toward the agent is considered to be positive. If the emotions were negative or changing from positive to negative, the attitude is classified as negative. The general attitude toward an agent is calculated as a ratio of conversations with positive tendencies to negative tendencies.

The information acquired this way (the user's general engagement in conversation and orientation of his/her attitude to the agent) provide an overview of the user's sentiment about the agent and is utilized as the second type of evaluative reasoning - about the agent.

4 SUB-SYSTEMS USED

To fulfill the implementation conditions for the database management system, and eventually perform both types of the evaluative reasoning we applied a set of sub-systems developed during this research project.

4.1 Affect analysis system - ML-Ask

ML-Ask is a system for affect analysis of utterances in Japanese. It is language-based and was constructed by Ptaszynski and colleagues [16] as an automatic affect annotation system for large corpora. The ML-Ask system uses a two-step procedure:

1. Analyzing the general emotiveness of utterances by calculating the emotive value;
2. Recognizing the particular emotion types in utterances described as emotive.

ML-Ask is based on the idea of two-part classification of realizations of emotions in language into:

1) *Emotive elements* or *emotemes* (ML), which indicate that emotions have been conveyed, but do not detail what specific emotions there are. This group is realized by such subgroups as interjections, mimetics, and vulgar language. Examples are: *sugee* (great!), *wakuwaku* (heart pounding), *-yagaru* (a kind of verb vulgarization);

2) *Emotive expressions* (MX); parts of speech that describe emotional states in emotive sentences. This group is realized by such parts of speech as nouns, verbs or adjectives. Examples are: *aijou* (love), *kanashimu* (sadness), and *ureshii* (happiness).

On textual input provided by the user, two features are computed in order: the emotiveness of an utterance and the specific type of emotion. To determine the first feature, the system searches for emotive elements in the utterance to determine whether it is emotive or non-emotive. In order to do this, the system uses MeCab for morphological analysis and separates every part of speech [17]. MeCab recognizes some parts of speech we define as emotemes, such as interjections, exclamations or sentence-final particles, like *-zo*, *-yo*, or *-ne*. If these appear, they are extracted from the utterance as emotemes. Next, the system searches and extracts every emoteme based on the system's emoteme databases (containing 907 items in total). All of the extracted elements mentioned above (exclamations from MeCab, emotemes and emoticons) indicate the emotional level of the utterance.

Secondly, in utterances classified as emotive, the system searches for the expressions describing emotional states using an emotive expression lexicon [18]. This determines the specific emotion type (or types) conveyed in the utterance. An example of analysis performed by ML-Ask (system output) is shown below.

(1)	*Kyo wa*	*nante*	***kimochi ii***	*hi*	*nanda*	*!*
	Today:TOP	ML:nante	**MX:joy**	day:SUB	ML:nanda	ML:!

Translation: Today is such a nice day!

(2)	*Iya∼,*	*sore*	*wa*	*sugoi*	*desu*	*ne–*	*!*
	ML:iya∼	this	:TOP	ML:sugoi	COP	ML:ne–	ML:!

Translation: Whoa, that's great!

(3)	***Hitoribocchi***	*nante*	***iya***	*da*	*∼∼*
	MX:sadness	ML:nante–da	**MX:dislike**	COP	ML:∼∼

Translation: Being alone sucks...

4.2 Emoticon analysis system - CAO

CAO is a system for estimation of emotions conveyed through emoticons developed by Ptaszynski and colleagues [19]. Emoticons are - sets of symbols widely used in text-based online communication to convey emotions. The CAO, or *emotiCon Analysis and decOding of affective information* system extracts an emoticon from an input (a sentence) and determines specific emotion types expressed by it using a three-step procedure. Firstly, matching the input with a predetermined raw emoticon database containing over ten thousand emoticons. The emoticons, which could not be estimated with only the database are automatically divided into semantic areas, such as representations of "mouth" or "eyes", basing on the idea of *kinemes*, or minimal meaningful body movements, from the theory of kinesics [20, 21]. The areas are automatically annotated according to their co-occurrence in database. The annotation is firstly based on eye-mouth-eye triplet. If no triplet was found, all semantic areas are estimated separately. This provides hints about potential groups of expressed

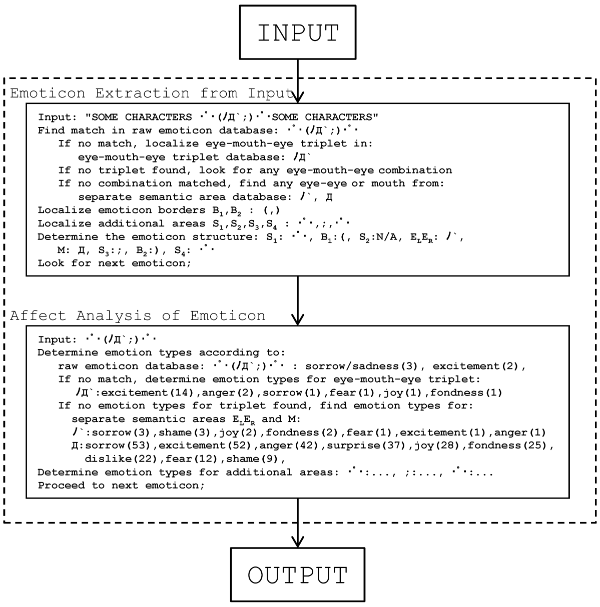

Figure 2. Description of main procedures in CAO.

emotions giving the system a coverage of over 3 million possibilities.

CAO is used as a supporting procedure in ML-Ask to improve performance of the affect analysis system.

4.3 Web mining technique

Shi and colleagues developed a technique for extracting emotive associations from the Web [22]. It takes as an input a sentence and in the Internet searches for emotion types associating with the sentence contents. Ptaszynski interprets this as an online commonsense reasoning about what emotions are the most natural and appropriate to appear within a certain context of an utterance [13]. The technique is composed of three steps: **a)** phrase extraction from an utterance; **b)** morpheme modification; **c)** extraction of emotion associations.

In the first step, an utterance after being analyzed morphologically by part-of-speech analysis tool for Japanese - MeCab [17], and n-gram phrases for further processing are composed using parts of speech separated by MeCab as unigrams. Secondly, the list of n-gram phrases ending with a verb or an adjective modified grammatically by adding causality morphemes. They distinguished five most frequently used morphemes stigmatized emotively in the Japanese language: *-te, -to, -node, -kara, -tara,* for which the coverage of the Web exceeded 90%. Finally, the modified phrases are queried in Google search engine with 100 snippets for one morpheme modification per query phrase. This way a maximum of 500 snippets for each queried phrase is extracted from the Web and cross-referenced with the emotive expression lexicon [18]. The higher hit-rate an expression had in the Web, the higher was the naturalness of the emotion type it represents.

However, as the Web mining process was time consuming, we decided to construct a robust emotion object database to make the Web mining technique into a stand-alone system.

Table 2. Example of emotion association extraction from the Web and its improvement by blog mining procedure.

Sentence: *Konpyuuta wa omoshiroi desu ne. (Computers are so interesting.)*	
Extracted emotion type	**Type extracted / all extracted types(Ratio)**
liking	79 / 284 (0.287)
surprise	30 / 284 (0.105)
excitement	30 / 284 (0.105)
fear	29 / 284 (0.102)
...	...

```
<emotion type: haji [shame] (202678 EmObj;
    4006378 SemCat)>
    <emotive expression: sekimen [turn red/feel
    ashamed] (2316 EmObj for this EmoExp)>
        Sentence<20 Japanese characters>:
        "Chakku wo shimeru no wasureta to ki ga
        tsuitara sekimen shita..."
        ["I turned all red when I noticed I
        had a fly open..."]
           EmObj: <Chakku shimeru no wasureta
               to ki ga tsuita> [Notice to
               have a fly open]
           CausInf: <tara> [because]
           EmoExp: <turn red/feel ashamed>
    ...
<emotion type: yorokobi [joy] (6123947 EmObj;
    120068119 SemCat)>
    <emotive expression: ureshii [happy]
    (1078312 EmObj)>
         ...
    <emotive expression: ureshimi [joyfulness]
    (5 EmObj)>
         ...
    ...
...
```

Figure 3. A structure of the emotion object database with examples.

4.4 Emotion object database - INFOE

From a blog corpus containing over 350 million of sentences we extracted and implemented a robust ontology-type database of emotion objects - INFOE (*I kNow Formal Objects of Emotions*), containing 19,459,167 of unique emotion objects. Their distribution among emotion types is shown in table 3. A structure of the database including some examples is described in Figure 3. The data in the database is formalized in three ways, using:

1. Statistics of the length of Emotion Object phrases;
2. Syntactical POS tagging and dependency structure;
3. Calculating the number of semantic categories of words appearing in the database;

4.4.1 *Sentence Length Based Statistics*

The statistics of the Emotion Object phrase length was calculated for each emotion type (see table 3), as well as for each emotive expression used as a seed in emotion object extraction. This part of information in the database represents statistical probability of emotion affiliation of an input generated by a user during interaction with the conversational agent.

4.4.2 *POS Tagging and Dependency Structure*

The POS tagging of the database was done by MeCab [17]. Dependency structure analysis is done by CaboCha, an SVM supported

Table 3. Distribution of number of emotion objects and semantic categories among emotion types.

Emotion type (No. of expressions	Number of extracted: emotion objects	semantic categories
joy (224)	6123947	120068119
relief (106)	3321795	66605209
dislike (532)	2957596	59136703
fondness (197)	2441865	45816845
fear (147)	1184952	23490755
excitement (269)	1104998	23102117
sadness (232)	930698	18911960
surprise (129)	898138	18164806
anger (199)	292500	5966179
shame (65)	202678	4006378

dependency structure analyzer for the Japanese language [23]. The information provided by both syntactical analyzes verifies the probability statistics calculated on the basis of the number of characters.

4.4.3 Semantic Formalization

The semantic formalization of the database is performed using *Bunrui Goihyo* - word list including semantic categories of words. The categories include such labels as: "Abstract objects", "Human Activities", "Natural Objects and Phenomena", "Subject of Actions", etc. Each main category consists also of number of sub-categories. The distribution of the number of categories according to their appearance for each emotion type is presented in Table 3.

5 IMPLEMENTATION PROCEDURE AND DIRECTIONS

In the process of database management there are two important phases, generation of new CU and management of the CU already existing in the database. The general description of CU management procedure has been explained in section 2. A procedure for generation of new CUs has been represented in Figure 4.

Every utterance of both, the user and the agent is preprocessed to create a model of the conversation. First the utterance is preprocessed by morphological analyzer MeCab and dependency parser CaboCha to generate information about syntax of the utterance, which represents one conversational strategy. Analysis of all utterances during the conversation create a conversational strategy model of this particular conversation.

Together with the syntactical analysis, analysis of emotions takes place. The utterance is analyzed with affect analysis system ML-Ask to specify the emotion type expressed by the user. After that, the emotion is verified whether it is appropriate for its object (utterance context). This is done first by looking up the appropriate emotions in INFOE database of emotion objects, and when no emotion associations are found, the system uses a Web-mining technique to obtain such associations from the Internet. The two above information (expressed emotion and its appropriateness for the context) make up the model of emotional strategies applied in this conversation.

The conversational strategy model and the emotional strategy model constitute the Context Unit (CU). Every CU is saved in the database preserved in XML format and is assigned a time stamp T and an emotional value E being an approximation of emotive values of user utterances. In the later process of forgetting, the decision of whether to keep the CU active, or deactivate it will be based on a value V derived from a function of these two intermediate values, as in equation 1. At present, however, it is not yet decided what type of function would be the most appropriate function and what should be the threshold of maintaining activation of the CU.

$$V = f(T, E) \tag{1}$$

In subsequent conversation previous active CUs, will be queried to find a CU matching user utterance. The matched features will be the conversation and the emotional strategies models. The agent's response will be generated using the strategies from an utterance subsequent to the user utterance in the database. Since the query will be made only on the active CUs (a subset of the whole database), the query time will be reduced.

The database management system is planned to be implemented in a counselor-companion agent meant to help users manage their emotions through a non-goal-oriented free conversation, or small talk [29]. We have performed some preliminary experiments in this direction with conversational agents. We found out that by adding modality to the agent's responses makes them more natural [24]. Secondly, assuming that the agent-companion should be also able to induce positive emotions in user, e.g., by a humorous response, we showed that implementation of a joke generator in a conversational agent greatly improves its impression [30]. Finally, we showed that a conversational agent using its conversation history (or CUs) to summarize previous conversations is perceived as more intelligent and makes the impression of listening to the user [31].

6 CONCLUSIONS AND FUTURE WORK

In this paper we presented the description of a dynamic database management system for conversational agents. The system borrows the idea from the process of forgetting in humans and is meant to improve the performance and naturalness of speech in conversational agents. The core of the system, forgetting and recalling algorithms, depend on frequency of usage of context units and their emotive values derived from evaluative reasoning about both sides of interaction - the agent and the user.

During the last several years we have been developing the intermediary systems to be implemented in the forgetting-recalling algorithm. We have first proposed the affect analysis system ML-Ask to estimate the emotive value of user's utterances [16]. Secondly, to improve the performance of the affect analysis system we proposed the emoticon analysis system CAO [19]. These two systems are combined in the algorithm of evaluative reasoning of the agent. Furthermore, a Web mining technique has been proposed to extract emotions associating with the context of an utterance [22]. To improve the performance of this method and shorten the time of processing we created an emotion object database. The affect analysis system together with Web mining technique are finally responsible for evaluative reasoning of the user [13].

As all parts of the systems needed in the implementation conditions of the dynamic database management system have been developed, at this moment we are working on combining the subsystems into the database indexing and management system. In the final implementation the database management system will operate on a database of a conversational agent-companion. The baseline for the conversational agent was already developed by Higuchi and colleagues [24] and improved further by Dybala and colleagues [25].

After combining together all parts of dynamic database management system we plan a test phase, where efficiency and performance of the system with the forgetting-recalling algorithm activated and

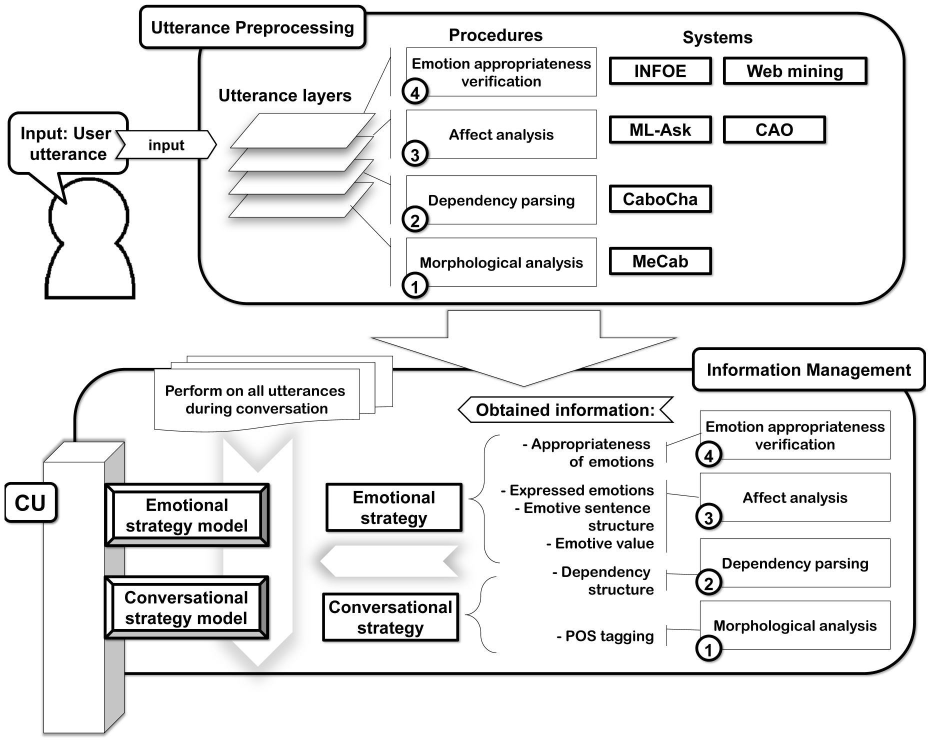

Figure 4. Description of the procedure for CU generation.

deactivated will be compared. In the test phase, naturalness and adequacy of speech will be tested with a standard usability test including several users testing the system for several days.

Fading of the unused context connections would improve agent's performance in processing large database containing context-bound sentences. Since, using the forgetting-recalling algorithms, the database is renewed according to the present needs, the agent after the training phase will operate on an always actual and appropriate database. In the final effect, the agent operating on the database management system presented in this paper should obtain a comparable with humans ability to process language.

Today we are surrounded by various artifacts based on "weak AI" [26, 27]. Card readers, red-eye and handshake effect reduction in our digital cameras, cellular phones, etc. make our lives easier. However, if we wish to create an intelligent interlocutor based on the "weak AI", that is, a program that would be, using Lyons' nomenclature [28], able to send messages informative for the receiver, but without knowing its communicative meaning (as a non-thinking machine), our attention should be paid on creation of an imitation of human way of thinking beginning with its originality, as well as with its all vices and weaknesses. We should not consider the artificial mind as a perfect creation. On the contrary, we should accept it with all its imperfections and defects. It cannot be excluded that some of them, such as forgetting, will eventually turn out to be merits.

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